Remote Sensing of gully erosion in the communal lands of Okhombe Valley, Drakensberg, South Africa.

By

Nosipho Pearl Makaya

Submitted in fulfilment of the academic requirements for the degree of Master of Science in the School of Agricultural, Earth and Environmental Sciences, College of Engineering, Agriculture and Science,

University of KwaZulu-Natal,

Pietermaritzburg

2018

Abstract

The main aim of this study was to assess remote sensing applications for detecting and mapping the spatial distribution of gully erosion in the communal lands of Okhombe Valley, Drakensberg, South Africa. The study first sought to review the progress of remote sensing by examining its usage and users over the years. The findings showed that the application of remote sensing for soil erosion studies has significantly increased by 45% since the 1960s. Although remote sensing is becoming widely accepted by a growing number of scientific disciplines, there is paucity in African lead authors and this call for more collaborative research and knowledge transfer. Literature further shows that Landsat series data is a popular remote sensing system used for soil erosion monitoring and mapping, mainly due to its multispectral bands and archival data. Although, commercial high resolution satellites have been demonstrated to accurately map small soil erosion features; their high acquisition costs remains a challenge, especially in resource constrained regions. Therefore, this allows for the exploration of the freely available new generation sensors for gully erosion mapping at regional scales. The second objective of the study was to evaluate the potential of the Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies. The study further investigated environmental variables (i.e. slope, vegetation cover, TWI and SPI) that may have a potential influence on gully initiation and development. The study evaluated the effectiveness of the Sentinel-2 spectral bands in discriminating gullies from other land cover types using the Support Vector Machine. The overall classification accuracy achieved for gully discrimination was 77% and all 10 Sentinel-2 spectral bands were selected as the ideal variables for discriminating gullies from other land cover types. Additionally, the findings of the study indicated that there is no significant difference between the environmental variables across different gully volumes and that all the measured variables have a weak influence on the volume of soil loss (i.e. Slope (R^2 = 0.02); Vegetation cover (R^2 = 0.01); TWI (R^2 = 0.11) and SPI (R^2 =0.02) despite an observable trend of influence. Overall, Sentinel-2 has demonstrated its usefulness in detecting and mapping gullies and it is therefore recommended that future studies explore the use of the freely available sensor in monitoring mapping soil erosion at regional scales.

Preface

The experimental work described in this dissertation was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, under the supervision of Professor Onisimo Mutanga. This dissertation represents original work by the author and has not otherwise been submitted in any form for any degree or diploma to any tertiary institution. Where use has been made of the work of others, it is duly acknowledged in the text.

Declaration - Plagiarism

I, Nosipho Pearl Makaya, declare that

1. The research reported in this dissertation, except where otherwise indicated, is my original research.

2. This thesis has not been submitted for any degree or examination at any other university.

3. This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

4. This dissertation does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a. Their words have been re-written but the general information attributed to them has been referenced

b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks, and referenced.

5. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged, and the source detailed in the text and in the reference section.

Nosipho Makaya (Student) Prof O. Mutanga (Supervisor)

…………………………. …………………………..

Table of Contents

List of Tables

List of Figures

Abbreviations

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
ENVISAT	Environmental Satellite
ERS	European Remote Sensing
ETM	Enhanced Thematic Mapper
GIS	Geographic Information Systems
IRS-LISS	Indian Remote Sensing- Linear Imaging Self Scanning
JERS SAR	Japanese Earth Resources Satellite Synthetic Aperture Radar
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
NIR	Near-Infrared
NOAA/AVHRR	National Oceanic and Atmospheric Administration/Advanced Very High Resolution Radiometer
RADARSAT	Radar Satellite
SARVI	Soil and Atmospheric Resistant Vegetation Index
SPOT (HRV/HRG)	Satellite Pour l'Observation de la Terre (High Resolution Visible/High Resolution Geometric)
SRTM	Shuttle Radar Topography Mission
SWIR	Short-Wave Infrared
TM	Thematic Mapper
TRMM	Tropical Rainfall Measuring Mission

Dedication

For my family

Acknowledgments

First and foremost, all glory to the Lord, the Almighty, for His showers of blessings throughout my studies.

I would like to extend my gratitude to the University of KwaZulu-Natal, for giving me an opportunity to pursue my Masters programme. Above all, I thank all members of staff (technical and academic), University of KwaZulu-Natal, Pietermaritzburg for their assistance.

A special thank you to the National Research Foundation (NRF) for funding my Masters programme and to the Water Research Commission (WRC) for providing field logistics support.

I would like to extend my most sincere gratitude to the following individuals. This research would not have been completed without the guidance of my research supervisor, Professor Oni Mutanga. His professional manner, enthusiasm and commitment thought my research is highly acknowledged. My appreciation also goes out to Dr Timothy Dube and Dr Khoboso Seutloali for their support, mentorship and encouragement through my studies.

To my dear friends and colleagues, thank you for the great laughs, memories and support. You sure made these years bearable and I will treasure the memories and inspiring interactions we've shared. A special thanks to Trylee, Tatenda, Sanele and for their field work assistance. Most of all, to Kusasa Sithole, thank you for giving the strength and hope to complete this MSc - you were always beside me during the happy and hard moments to push and motivate me.

To my beloved parents and family, I dedicate this Masters thesis to you. You are my backbone and I am deeply grateful for all your sacrifices, continual support, encouragement and unconditional love.

Last but not least, to Institute of Natural Resource (INR) and its staff. Thank you for the professional exposure and support you've provided me thus far. I deeply appreciate it.

CHAPTER ONE

General Introduction

1.1. Background

Land degradation in the form of soil erosion by water has been significantly documented around the world as a critical driver of environmental change (Ananda and Herath, 2003; Poesen *et al*., 2003; Lal, 2001; Valentin, Poesen and Li, 2005). Gully erosion is one of the most severe forms of water erosion and has received a great deal of attention, due to its destructive nature. Gully erosion is associated with negative off-site and on-site effects, such as causing a decline in soil productivity and quality (Pimentel and Burgess, 2013) thereby affecting agricultural production and sedimentation of rivers and reservoirs (Poesen, 2011) consequently reducing water holding capacity and quality. For example, it has been reported that gullies are increasingly affecting agricultural lands and account for an estimated soil loss range of 1248–23 400 million tons per year from 78 million ha of pasture, rangelands and cultivated fields across Ethiopia (Hawando, 2001; Daba *et al*., 2003). In South Africa, De Villiers and Basson (2007) reported that sedimentation had reduced the Welbedacht Dam storage capacity to approximately 90% over a period of 30 years.

Although gully erosion is a natural process shaping the earth's landscape, in many countries, it has been observed that it is accelerated by unsustainable human activities, such as land use practices (Kakembo and Rowntree, 2003; Sonneveld *et al*., 2005; Smolska, 2007). In South Africa, gully erosion is largely a product of heavy rains and highly erodible solonetzic and dispersive soils (Laker, 2003). The communal lands of northern KwaZulu-Natal are one of the most severely affected parts of South Africa by gully erosion, due to steep topography and a history of land use change (Le Roux *et al*., 2008; Mararakanye and Le Roux, 2012). This increasingly causes a concern for catchment instability and water resource management. However, despite this information, little is still known about the extent of erosion and possible contributing environmental factors to gully initiation and development in South Africa as field methods are expensive and time consuming. Assessing the spatial distribution of gullies and quantifying possible gully influencing factors has thus become a requirement for cost effective conservation planning, facilitating the decision making process for suitable prevention and control measures especially at municipal and provincial levels (Marakanye and Le Roux, 2012).

To effectively address the problem of gully erosion, the assessment and monitoring of the spatial distribution of gullies is essential. In this context the use of remote sensing technology has the potential to provide a synoptic and timely analysis of the severity of soil erosion. Remote sensing is a robust tool that offers meaningful spatial data for the assessment and monitoring of spatio-temporal variations of soil erosion over large areas (Mathieu *et al*., 1997; Dwivedi *et al*., 1997; Haboudane *et al*., 2002; King *et al*., 2005, Vrieling, 2006; Liberti *et al*., 2009, Le Roux and Sumner, 2012). Remote sensing offers cost and time effective tools to accurately map erosion which often overcome the limitations of traditional soil erosion assessment methods (Vrieling, 2006; Lu *et al*., 2007; Liberti *et al*., 2009). Gully erosion maps, produced quickly and cheaply from readily-available data, are a useful tool in regional planning for erosion control (Taruvinga, 2009). Therefore, developing a robust, reliable and accurate means of mapping gullies is a current focus of this study. Literature shows that traditional mapping techniques through the manual digitization of aerial photographs and satellite imagery have been extensively used for the mapping and monitoring of gully erosion (e.g. Jones and Keech, 1966; Morgan *et al*., 1997; Fadul *et al*., 1999). However these techniques are time consuming and the datasets rarely provide sufficient information for gully mapping and monitoring as they are restricted to small scale (e.g. Jones and Keech, 1966; Servenay and Prat, 2003; Poesen, 2011).

Remote sensing advancements have provided tremendous capabilities for mapping gully erosion as fine resolution sensors, such as QuickBird, IKONOS and Worldview are increasingly becoming popular. Although these datasets have been documented to provide accurate results for gully mapping (e.g. Shruthi *et al*., 2011; Ranga *et al*., 2015; Le Roux and Marakanye, 2012), their application at a larger scale is limited due to their small swath width and high acquisition costs, which become a challenge for resource constrained regions. These shortcomings have shifted attention towards the application of freely available multispectral sensors such as Landsat datasets, characterised by a global footprint and continual coverage (Dube and Mutanga, 2015) and more recently launched Sentinel-2 MSI products. For example, Seutloali *et al*. (2017) demonstrated the usefulness of the freely available multispectral Landsat 8 OLI sensor in mapping the spatial variations of soil erosion at regional scale where extensive field-work remains limited. On the other hand, the recently launched Sentinel-2 MSI sensor offers improved spatial and spectral capabilities for repeated regional scale mapping and monitoring of soil erosion. For instance, a study by Sepuru and Dube (2018) demonstrated the effectiveness of Sentinel-2 in mapping spatial distribution of eroded area, achieving an overall classification accuracy of 81,90%. The study concluded that the Sentinel-2 MSI sensor's 5 day temporal and 10m spatial resolution make it an ideal primary data source for cost effective and practical soil erosion mapping and monitoring at regional scale, especially for resource constrained regions. Therefore, the current study aims to evaluate remote sensing applications for mapping the spatial distribution of gullies in Okhombe valley, Drakensberg, South Africa.

1.2. Aims and objectives

The overall purpose of the study was to evaluate remote sensing applications for mapping the spatial distribution of gullies in the communal landscape of Okhombe Valley, Drakensberg. The following objectives were set:

- To review the progress and identify gaps in remote sensing applications in soil erosion mapping using multispectral remotely sensed data
- To evaluate the potential of the recently launched freely available medium resolution Sentinel-2 MSI sensor in detecting and mapping gullies
- To investigate the possible environmental factors that influence the spatial distribution of gullies in Okhombe Valley.

1.3. General structure of the thesis

This thesis is presented in four chapters. The first chapter provides an outline of the study, drawing attention to the need for assessing the spatial distribution of gullies as a prerequisite for effective implementation of erosion control and rehabilitation measures. Chapter 2 of the study reviews the progress of remote sensing usage and users in soil erosion assessment at varying scales. The chapter highlights the progress of remote sensing applications for soil erosion studies through analysing the publication details including author affiliation, geographic location and scale of study and remote sensing systems and methods used. Chapter three evaluates the potential of the freely available multispectral Sentinel-2 MSI sensor for mapping the spatial distribution of gullies in Okhombe valley, Drakensberg. The study examined the effectiveness of the Sentinel-2 raw bands in discriminating gullies from other land cover types as well as investigate the possible environmental variables that influence gully initiation and development of the estimated soil loss for the identified gully.

The last chapter of the thesis reviews the research objectives and provides limitations and major findings of the study.

CHAPTER TWO

Remote Sensing of Soil Erosion: A literature review.

This Chapter is based on:

Makaya, N. P., Mutanga, O. & Dube, T. 2018. Remote Sensing of Soil Erosion: A literature review. *South African Geographical Journal*. RSAG-2018-0054 (Submitted).

Abstract

Soil erosion is widely recognised as a land degradation problem that poses a threat to the environment. To develop effective and robust soil erosion control mechanisms, regional scale assessment is a pre-requisite. However, this is being limited by the lack of data availability. Despite these limitations, researchers have made tremendous progress in soil erosion mapping and monitoring. Unfortunately, this information is poorly documented and to determine future research direction, there is a need to provide an overview on the progress to date. The aim of this work therefore was to investigate how the application of remote sensing for soil erosion analysis has developed over the years. The paper evaluates the usage and the users of remote sensing by focusing on three aspects of the material (104 peer-reviewed articles): publication details (year of publication, scientific discipline of journals and author national affiliation), geographic information (location and spatial scale of study) and data usage (application of remote sensing systems, methods and measures for accuracy assessments). Three key results were obtained: i) the application of remote sensing for soil erosion mapping has significantly increased since 1966 and is becoming accepted by an increasing number of scientific disciplines, (ii) the contribution of African lead authors is low, which could possibly indicate that knowledge transfer and technologies from developed countries is imbalanced, (iii) Landsat is the most commonly used remote sensing system and although its spatial resolution is a limitation, its multispectral bands and archival data make it ideal for soil erosion detection and monitoring. Therefore, this literature review emphasises the need for collaborative research that could possibly explore the potential and further enhance the usefulness of satellite technology in answering pertinent geomorphology and soil conservation research questions.

Key words: runoff, soil erosion, remote sensing, monitoring, satellite data.

2.1. Introduction

Water erosion is widely recognized as a critical land degradation problem that increasingly impacts terrestrial and aquatic systems globally (Oldeman *et al*., 1991). For instance, soil erosion accounts for an estimated 85% of global land degradation (Angima *et al*., 2003). While soil erosion is a natural process, anthropogenic activities have significantly contributed to the acceleration of the process, consequently resulting in a dramatic decline of land resources (Lal, 2001). Environmental challenges caused by the acceleration of soil erosion are attributable to drastic changes of land use patterns. For instance, clearing of vegetation cover by over grazing, inappropriate farming techniques that cause soil crusting and compaction, as well as infrastructural development, such as roads generate high amounts of runoff consequently leading to soil erosion (Pimentel, 2006). Furthermore, onsite effects of soil erosion further cause negative downstream effects, such as sedimentation of dams and rivers, subsequently degrading water quality and quantity (Lu *et al*., 2007; Morgan, 2009).

Given the high spatial variability of soil erosion, it is vital to obtain spatial data depicting the severity of soil erosion, as well as understanding the dynamics that contribute to soil erosion for the implementation of soil conservation, planning and mitigation measures. Controlling and preventing soil erosion requires the implementation of biophysical measures often at field or catchment scale and Vrieling (2006) argues that obtaining such data at regional scales has been challenging, due to data scarcity. Field surveys, time constraints and challenging terrain provide a limitation for data availability and quality (Mather and Tso, 2016). Nonetheless, numerous studies that have mapped soil erosion risk at different scales across the world are often constructed using erosion models (Megahan *et al*., 2001; Ma *et al*., 2003; Rahman *et al*., 2009). However, Stroosnijder (2005) reiterates the challenge of data quality, noting that it is difficult to validate computed erosion rates due to the costly and strenuous nature of conducting accurate field measurements.

Remote sensing technologies on the other hand offer cheaper, continual and accurate large scale data for soil erosion assessment thereby overcoming the challenges associated with field methods (Vrieling 2006). The emergence of remote sensing technologies gained popularity in the exploration of the potential remote sensing products to facilitate in soil erosion research (Pickup and Nelson, 1984; Pickup and Chewings, 1988; Huete and Liu, 1994; Dwivedi *et al*., 1997; Sujatha *et al*., 2000; Martınez-Casasnovas, 2003; Guanglu *et al*., 2004). There is a plethora of optical and radar remote sensing technologies characterized with different spectral, spatial and temporal resolutions that have been applied in soil erosion related studies (see Table 2), including the commonly used Landsat series data. Remote sensing technologies are continuously being improved for better optimization, such as the recently launched European Space Agency (ESA) open access Sentinel satellite products (Kaplan *et al*., 2014). The advantages offered by open access data policies and low-cost software have provided a platform for a wide range of users to make use of remote sensing applications (Kaplan *et al*., 2014).

Four scientific literature reviews discussing the progress of remote sensing applications for soil erosion studies, providing an overview of the technological and methodological strengths and weaknesses were identified. For instance, a review by Bishop *et al*. (2012) evaluated studies carried out for deriving information on water and wind erosion using satellite data. While Vrieling (2006) reviewed different methods including validation techniques applied for water erosion assessment using satellite data and concluded that there is a paucity of validation data for soil erosion mapping. Mayr *et al*. (2016) on the other hand provide an overview of issues related to the application of remote sensing technologies for the identification and mapping of land degradation features, focusing on Latin America and Caribbean region. Karami *et al*. (2015) provide a critical analysis of remote sensing methods for detecting soil degradation, including soil erosion by runoff reflecting on the importance of improving wide regional detection.

In contrast to the studies presented above, this current literature review provides a quantitative analysis of the progress of remote sensing applications for soil erosion assessment over a period of 50 years. Water erosion occurs in various forms however the focus of this literature review is only on sheet, rill and gully erosion, thus excludes landslides and floodplain erosion. The objective of this literature review therefore is to provide a comprehensive overview of the usages and users of remote sensing to study soil erosion processes. The literature review analysis further examine researchers who have used remote sensing applications in soil erosion studies. Publication details (year of publication, scientific discipline of journals and author national affiliation), geographic information (location and spatial scale of study) and data usage (application of remote sensing systems and procedures for accuracy assessments) for each research article were examined. This will facilitate in identifying trends and gaps in the usage and users of remote sensing and subsequently determine areas that require prioritising (Karlson and Ostwald, 2016), and thus improving the effectiveness of remote sensing for soil erosion monitoring.

2.2. Erosion controlling factors

Soil erosion is a complex process that is controlled by various interrelated environmental parameters i.e. bedrock type, soil, climate, vegetation, topography and land use. Understanding the dynamics driving soil erosion facilitates in determining the rate of change and period required to update soil erosion maps (Vrieling, 2006). The detection of eroded areas and erosion features together with the assessment of controlling factors can be studied through the integration of spatial data, topographic maps, field surveys, aerial photographs and satellite imagery (Lawrence and Ripple, 1998). Remote sensing applications for soil erosion studies often evaluate erosion controlling factors, in addition to the detection of erosion features and eroded areas (Le Roux, 2011). For instance, satellite data are used to derive soil conditions, vegetation cover, and topography and land use characteristics that are often used in soil erosion models. However, only studies that use remotely sensed data to assess these erosion contributing factors are discussed in this section.

A few studies use satellite applications for the assessment of rainfall characteristics in soil erosion studies. For example, Vrieling *et al*. (2008) performed a regional erosion risk analysis using large scale Moderate Resolution Imaging Spectroradiometer (MODIS) derived Normalized Difference Vegetation Index (NDVI) and TRMM to estimate rainfall erosion periods. The study compared the NDVI time series vegetation signatures with rainfall data from Tropical Rainfall Measuring Mission (TRMM) and was able to determine the most critical periods for erosion risk. Although coarse resolution data such as MODIS offer high spectral and temporal resolution for soil erosion risk assessment, such large scale coarse resolution data present challenges for erosion mapping. For instance, not only is it challenging to detect erosion features at field scale due to its low spatial resolution of 1KM, MODIS also presents implications of low image acquisition particularly for tropical regions owing to its low availability of cloud-free data.

2.2.1. Topography

One topographic feature that typically contributes to the erosion process is the degree of slope where a steeper slope results in increased velocity of runoff thereby initiating erosion (Jain and Goel, 2002; Valentin *et al*., 2005). For instance, a study by Seutloali *et al*. (2016) found that soil erosion occurs on steeper slopes that are greater than 30m. In contrast, Guanglu *et al*. (2004) found that shallow gullies that are 0.3–2 m deep generally occur on the lower and middle areas of the slope and rill erosion in the upper/ middle areas.

Spatial erosion models often require a Digital Elevation Model (DEM) to extract topographic data, such as slope characteristics. Traditionally, DEMs are constructed using contour lines from topographic maps or from aerial photographs stereo pairs (Betts and DeRose, 1999; Martınez-Casasnovas, 2003; García-Ruiz, 2010) and more recently from high-resolution digital aerial imagery. For example, a study by Huete (1988) monitored soil surface change of rangeland erosion using a DEM obtained from a high-resolution aerial imagery and successfully identified surface elevation change. The advancement of remote sensing technologies set precedence for satellite data to offer good quality DEM of less than 20m resolution provided by the SPOT stereo optical imagery or Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (Toutin and Cheng, 2002). For example, Haboudane *et al*. (2002) generated slope and topographic curvature from a Satellite Pour l'Observation de la Terre High Resolution Visible (SPOT HRV) derived DEM while Cyr *et al*. (1995) also used a DEM derived from SPOT HRV for the visual interpretation analysis of erosion features.

On the other hand, interferometric Synthetic Aperture Radar (SAR) imagery with spatial resolution of 30m, such as the European Remote Sensing satellite (ERS), Environmental Satellite (ENVISAT), and TerraSAR-X have also been used for erosion detection. For example, Nanni *et al*. (2012) were able to study erosion processes by performing a morphometric analysis based on slope aspect, flow accumulation, stream network and lithology derived from the ERS SAR interferometric DEM of 20m. Bouaziz, *et al*. (2011) on the other hand, recently used geomorphologic factors derived from Shuttle Radar Topography Mission (SRTM) and ASTER DEMs to describe the geomorphologic setting and shapes of gullies. The study found that ASTER derived DEM of 15 m improved the accuracy in identifying gullies over small scales as opposed to the 90m SRTM data DEM. Hence, the use of remote sensing demonstrates the feasibility of providing information for soil erosion vulnerability.

2.2.2. Soil

Soil erosion is influenced by a range of soil properties, such as texture, structure, moisture, roughness, and organic matter content that determine the soils aggregate stability (Vrieling, 2006). These soil properties can be determined using infrared and visible sensors, often examined by visual interpretation and image classification. Differences in soil erodibility can be studied by analysing the spectral behaviour of soils provided by the satellite imagery (Reusing *et al*., 2000). For example, a study by Wang *et al*. (2003) successfully mapped the spatial distribution of soil erodibility using extrapolated erodibility values assigned in the field and Landsat TM band 7. Singh *et al*. (2004) on the other hand, found significant relationships between soil colours defined by the Munsell system and Landsat satellite imagery. Moreover, the soil's spectral reflectance is significantly influence by topsoil characteristics such as soil colour, iron oxides, moisture content etc. (Toutin and Cheng, 2002). For example, Nanni *et al*. (2012) were able to determine and discriminate soil classes using discriminant analysis of spectral data derived from Landsat imagery. The results of the study confirmed the practicability of identifying individual soil classes using spectra data obtained from the surface for soil classification.

Mathieu, *et al*., (1997) noted that although topsoil characteristics can be a limitation for determining one specific property, they can however be effective in determining soil crusting as the removal of topsoil by soil erosion causes a decline of organic matter and iron oxides, consequently uncovering subsoil (De Jong *et al*., 1999). For example, Singh *et al*. (2006) assessed the level of soil degradation by estimating soil colour from NOAA/AVHRR satellite data. Soil colour was determined using various vegetation indices, such as NDVI and MSAVI and a correlation was found between soil colour and vegetation indices. Since erosive processes alter the soil's physical and chemical properties subsequently changing the colour, studying soil colour from satellite data can be beneficial in monitoring soil erosion processes Singh *et al*. (2006).

Optical satellite data however can present a limitation in measuring topsoil reflectance due the vegetation interference (Lawrence and Ripple, 1998). Radar satellite data on the other hand can overcome this challenge as they provide spectral information beyond vegetation and soil surface in instances where soil erosion is exacerbated by surface crusting (Vrieling *et al*., 2008; Wulf *et al*., 2014). Soil surface roughness initiates and accelerates erosion, due to the high runoff volumes that collects downslope (Valentin *et al*., 2005, King *et al*., 2005). SAR data can provide useful information on erosion processes radar satellites are sensitive to soil roughness and moisture. For example, a study by Baghdadi *et al*. (2002) investigated the potential of SAR data derived from ERS and RADARSAT sensors for determining possible runoff and soil erosion in northern France. The study found that the SAR data could determine the influence of soil roughness on soil erosion, thereby successfully discriminating and mapping various surface roughness classes (smooth, medium and rough) over agricultural fields.

2.2.2. Vegetation cover

Vegetation cover is considered as one of the most important factors controlling soil erosion and can considerably decrease soil loss, due to its ability to bind soil particles, thereby protecting the soil (Jain and Goel, 2002; Lawrence and Ripple, 1998). Remote sensing facilitates in identifying and studying land cover features based on their spectral characteristics (Vrieling, 2006). Healthy vegetation and dry bare soil have significantly different spectral characteristics in the visible and near-infrared regions of the electromagnetic spectrum, where the latter is generally indicated by a stable reflectance in both regions (Vrieling, 2006). The classification and mapping of vegetation is therefore an essential step towards an understanding of vegetation cover and its relationship with soil conditions.

Vegetation indices have been widely used to study vegetation and soil conditions in erosion studies and provide a quick and simple technique for erosion feature extraction (Mathieu *et al*., 1997; Del Valle *et al*., 1998; Botha and Fouche, 2000, Alatorre and Beguería, 2009; Meusburger *et al*., 2010; Xue and Su, 2017; Ranga *et al*., 2012). Vegetation indices are derived from satellite data to discriminate vegetation and bare soils by maximizing on a linear relationship between the red and near-infrared bands (Taruvinga, 2009). NDVI is a popular vegetation index in soil erosion studies. For example, a study by Nadal-Romero *et al*. (2012) performed an analysis of various spectral indices in assessing badlands dynamics. The results of the study indicated a clear distinction between vegetated and eroded areas and the study recommended using the simplest and most commonly used spectral Index (NDVI). However, despite its wide recognition, studies have documented the drawbacks of NDVI, such as its the over-saturation in high density biomass, sensitivity to soil brightness, soil colour, cloud and cloud shadow (Cyr *et al*., 1995; Purevdorj *et al*., 1998; Mutanga and Skidmore, 2004;Govaerts and Verhulst, 2010). This consequently led to various modifications in efforts to overcome this disadvantage by reducing the soil effects of sparsely vegetated areas or bare soil (Xue and Su, 2017).

The Soil Adjusted Vegetation Index (SAVI) and Soil and Atmospherically Resistant Vegetation Index (SARVI) are one of most commonly used modifications of NDVI in soil erosion studies (Phinzi and Ngetar, 2017). Indices such as the SAVI, Modified Soil Adjusted Index (MSAVI) and Transformed Soil Adjusted Vegetation Index (TSAVI) were established in efforts to improve the detection of erosion features in areas with low vegetation (Taruvinga, 2009). For example, Phinzi and Ngetar (2017) used Landsat derived vegetation indices to compare the accuracy of NDVI, SAVI and SARVI in mapping soil erosion distribution in South Africa. The study yielded good accuracy results with a Producer's Accuracy of 77.5%, a User's Accuracy of 79.5% and a Kappa statistical accuracy of 64%. Similarly, Taruvinga (2009) assessed the utility of Landsat-derived vegetation indices namely NDVI, TSAVI and in mapping gullies at catchment level. The results of the study found that NDVI produced the highest accuracy for mapping gullies at sub-catchment level, whilst TSAVI successfully mapped gullies at catchment level.

2.3. Materials and Methods

This study was conducted based on a systematic quantitative literature review method which was adapted from Karlson and Ostwald (2016). The relevant articles that were identified were categorised and critically examined following the steps shown in Fig. 2.1.

2.3.1. Literature search

The literature searched included peer-reviewed articles published from 1966 up to mid-year 2017 that focused on the applications of remote sensing for soil erosion studies. These articles were systematically searched in scholarly electronic databases including Google Scholar, SCOPUS, Science Direct, EBSCOhost, and Web of Science and were additionally identified in relevant literature reviews and citation lists. The selection criteria included i) publication in a scientific journal, ii) geographical location of research conducted globally including the spatial scale and iii) the use of remote sensing data for water erosion analysis.

This literature review was limited only to literature concerning remote sensing of water erosion (specifically sheet, rill and gully erosion). The keywords used included “soil erosion”, “land degradation”, “soil degradation”, “remote sensing”, and “gully erosion”, “satellite data” and “water erosion”.

2.3.2. *Literature analysis*

Each article was examined and categorised based on the following information which was recorded in a Microsoft Excel database: 1) publication details consisted of the year of publication, scientific journal (based on aim of scope) and author’s national affiliation; 2) geographical location included study location and the scale of each which as was examined based on four categories i.e. i) regional, ii) catchment, iii) local; 3) data usage was examined based on the type of remote sensing instrument and method used. Information on whether each study performed accuracy assessment or not was recorded including validation applied for each study.

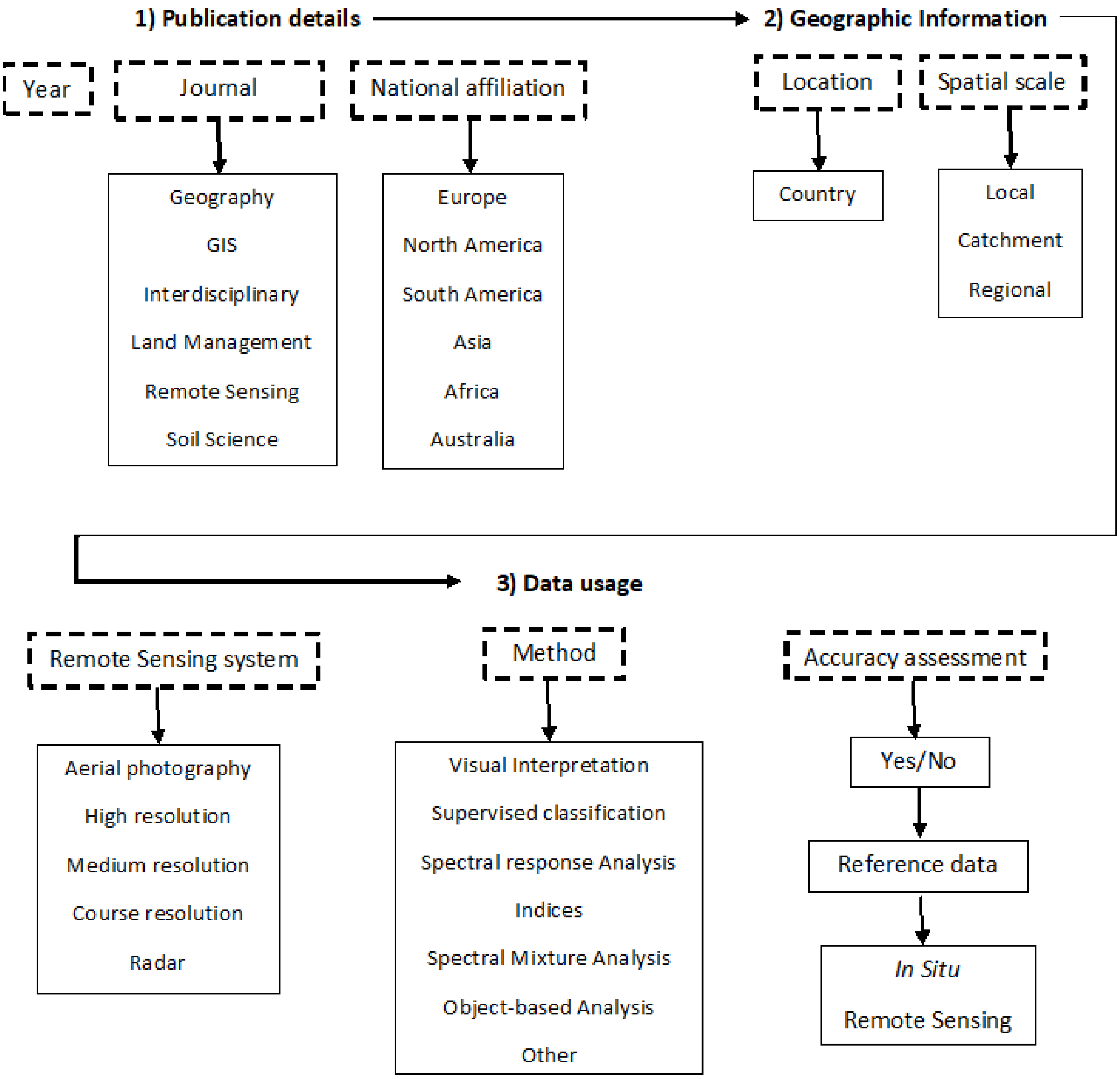

Fig. 2. 1: Flowchart describing the literature analysis process where the broken boxes indicate the categories used for examining the articles and the solid boxes indicate the sub-categories (Adapted from Karlson and Ostwald (2016)).

2.4. Results

2.4.1. Publication details

The review analysis reveals that remote sensing for soil erosion research gained more recognition from 1996, although the first publication occurred in 1966 as shown in Fig. 2.2. Only two papers were identified from 1966-1975 which mainly focused on mapping gully erosion. Since then the use of remote sensing for soil erosion mapping and monitoring has progressively increased, reaching 104 published articles by 2017 mid-year. A relative increase in publications can be observed from 1976-1985 where 8 research papers were identified and since then a significant increase of publication can be observed from 1996 onwards where 37 research papers were identified and 53 were identified from 2006 up to 2017 mid-year as shown in Fig. 2.2. In the recent 11 years (2006-2017), most studies have focused on gully erosion highlighting the increase of this erosion phenomena and its impact on water resources and food security.

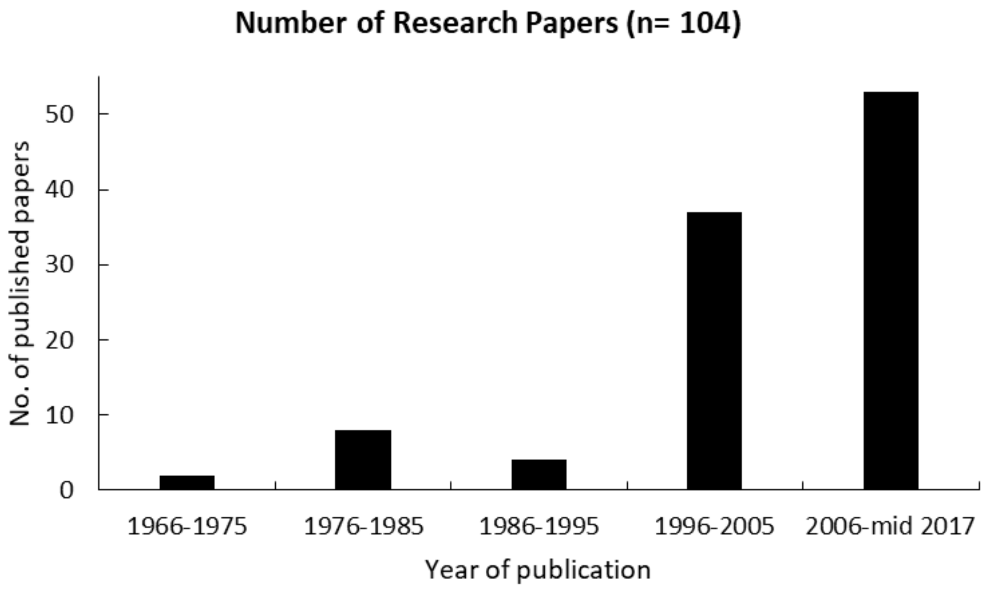

Fig. 2. 2: Temporal development of published articles where remote sensing has been used for soil erosion assessment.

Moreover, Table 2.1 indicates the distribution of research papers published in different journal categories over the years. The reviewed articles were published in 48 different scientific journals where both remote sensing and interdisciplinary journals published 36% of papers each by mid-year 2017. It can be observed that the 1966 up to 2005 research papers were mostly published in strictly remote sensing journals while the rest of the journal categories (i.e. Geography, GIS, Interdisciplinary, Land Management and Soil Science) were under represented. The use of remote sensing for soil erosion studies significantly increased from 2006 onwards, marking a change of interdisciplinary work. Interestingly, it can be observed that the application of remote sensing became widely accepted by other scientific disciplines as shown in Table 2.1 having 49% of papers published in interdisciplinary journals.

Table 2. 1: Temporal development of articles published in journal categories.

Journal category	**1966-1975**		**1976-1985**		**1986-1995**		**1996-2005**		**2006-2017 mid-year**		**Total**	
	No	%	No	%	No	%	No	%	No	%	No	%
Geography			2	25			4	11	11	21	17	16
GIS									1	2	1	10
Interdisciplinary					2	50	8	22	26	49	36	34
Land Management			1	13			7	18	3	6	11	10
Remote Sensing	2	100	5	63	1	25	16	43	12	23	36	34
Soil Science					1	25	2	6			3	2
Total no.	**2**		**8**		**4**		**37**		**53**		**10 4**	

2.4.2. Geographical Information

Fig. 2.3 illustrates the geographic spatial distribution of research papers that have applied remote sensing for the assessment of soil erosion. It can be observed that 12% of the studies were conducted in the semi-arid Mediterranean regions of Europe, mostly Spain, 10% of the studies were mostly conducted in Africa specifically South Africa and 9% of the studies were conducted in southern Asia (i.e. India). Fig. 2.3 illustrates the application of remote sensing across different spatial scales. A large proportion studies (85 studies) published from 2006 onwards were conducted at catchment scale while 16 papers were conducted at local scale and only 3 studies were conducted at regional/national scale as shown in Fig. 2.4. It can be observed that authors who are affiliated with European institutions mostly in Spain and Belgium published large portions of the studies (34 papers) as shown in Fig. 2.5 while authors affiliated with African institutions published 23 papers (mostly South Africa and Nigeria).

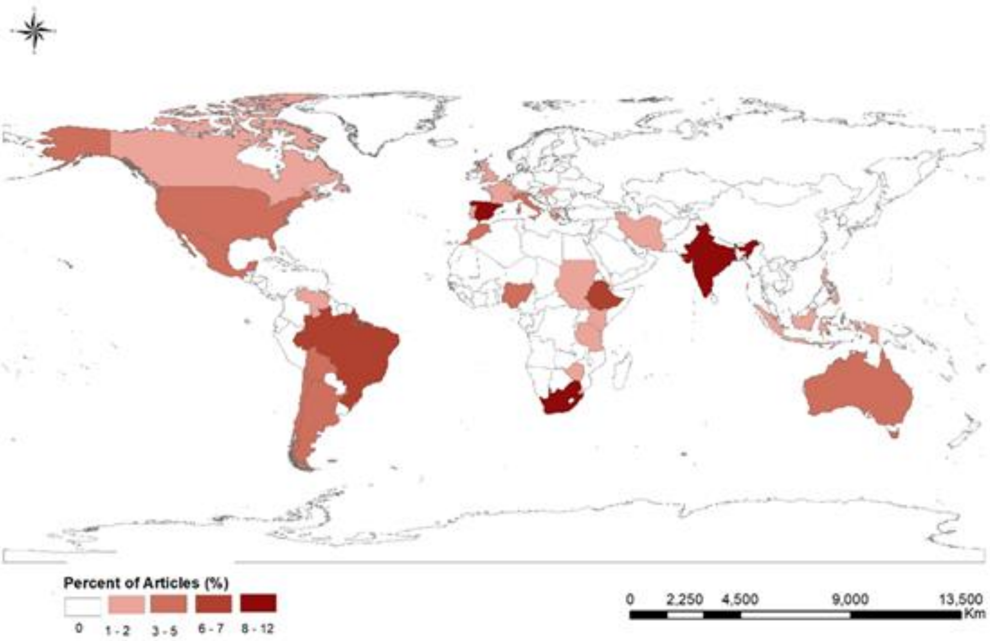

Fig. 2. 3: Percentage of published articles in each country.

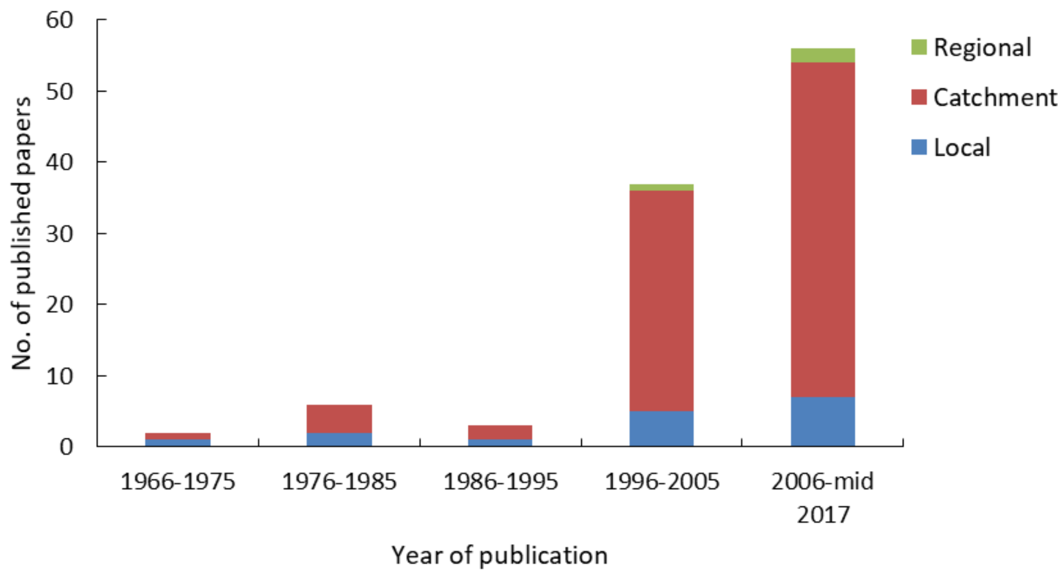

Fig. 2. 4: Temporal development of the spatial scale of each study.

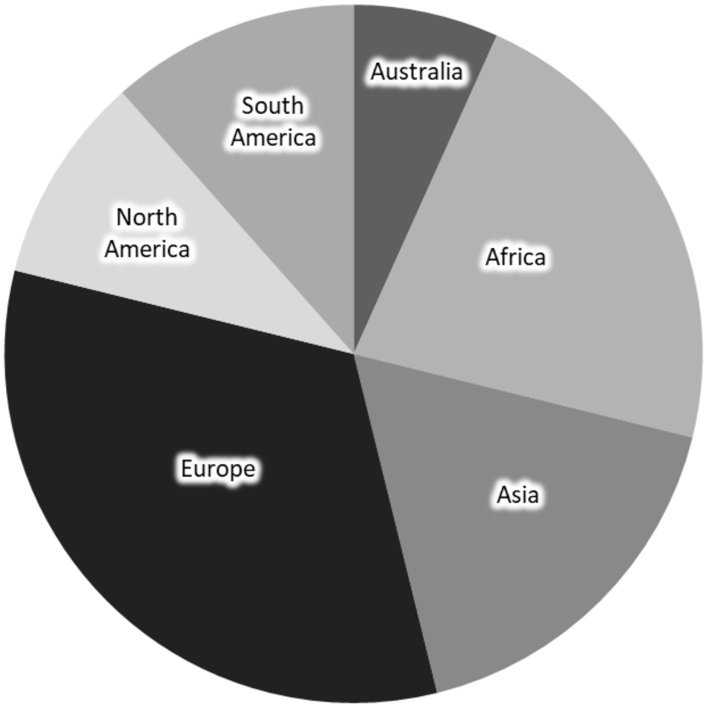

Fig. 2. 5: National affiliation of lead author.

2.4.3. Data Usage

Table 2.3 below shows an overview of optical and microwave radar satellite systems characteristics that have been used in erosion research while Figure 2.6 illustrates the reviewed 104 papers that have used different remote sensing systems for the mapping and monitoring of soil erosion. A wide range of optical and radar satellite systems characterized by different spatial resolutions were used for assessing eroded areas. The literature review analysis showed that 41% of the studies used optical medium resolution satellite imagery (i.e. Landsat) while 35% of the studies used aerial photographs, 12% used high resolution satellite imagery (mostly QuickBird and IKONOS) and only 9% used radar satellite imagery (mostly RADARSAT and JERS SAR).

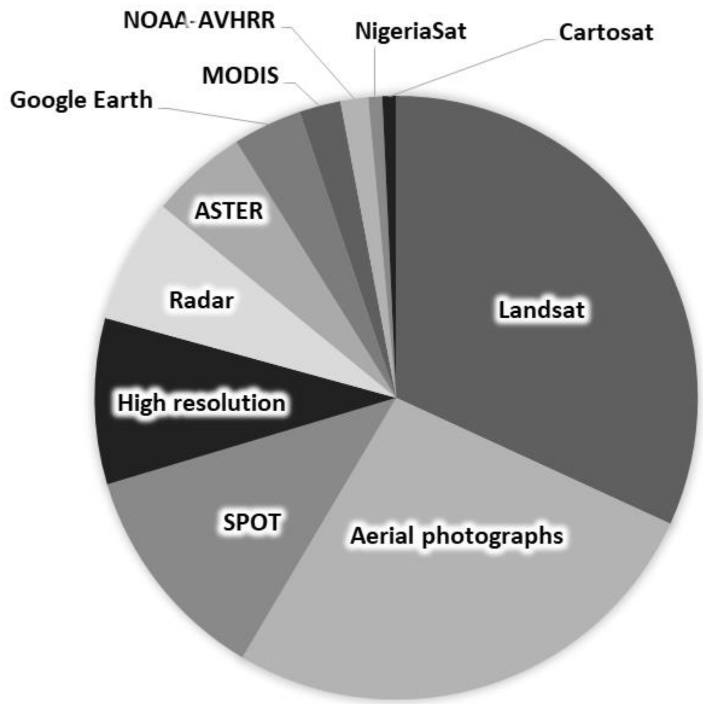

Fig. 2. 6: Remote sensing systems used to assess soil erosion.

Moreover, a range of processing techniques i.e. visual interpretation, supervised Maximum Likelihood Classifier (MLC), object-based analysis etc. were used for the mapping of eroded areas as shown in Fig. 2.7. 43 studies assessed areas affected by soil erosion using visual interpretation, while the MLC was the most commonly used traditional classification method and only 2 studies used the object-based method as shown in Fig. 2.7. It was further observed that validation of results was assessed using an independent reference dataset where 63% of the reviewed studies validated their results by in situ and remotely sensed data while 37% studies did not validate their results (Table 2.2).

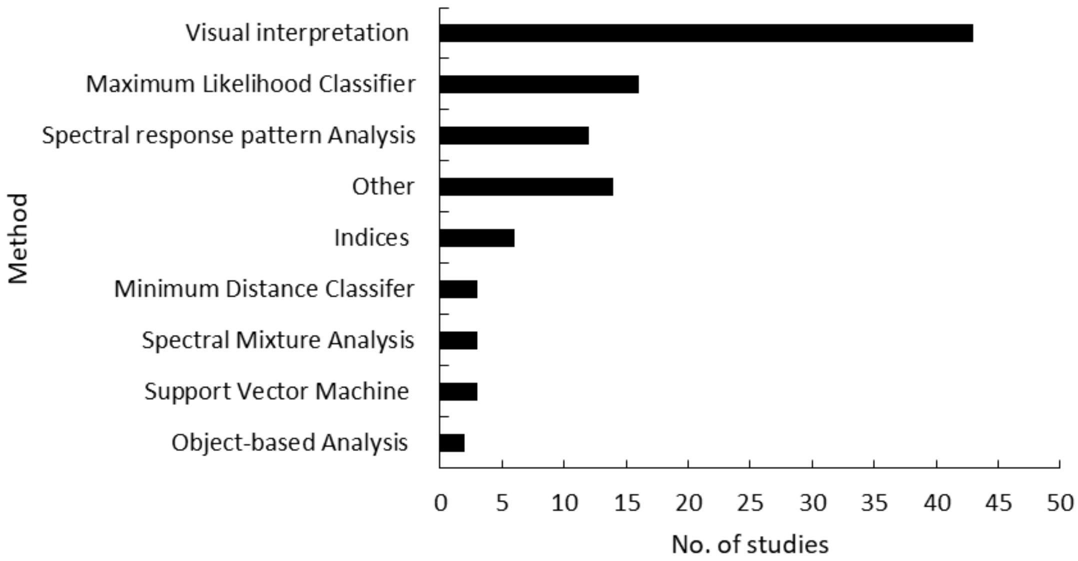

Fig. 2. 7: Remote sensing methods used for the detection and mapping of soil erosion.

Table 2. 2: Accuracy assessment performed for each study.

Accuracy assessment	**No. of studies**	**Percentage of papers (%)**
Yes	65	63
Reference data type		
In situ data	32	
Remote sensing	33	
No	39	37

Table 2. 3: Overview of remote sensing systems used in soil erosion studies.

Satellite	Sensor	Operation time	Spatial Resolution	Temporal Resolution	Spectral Bands
OPTICAL					
Landsat – 1, 2, 3	MSS	1972 – 1983	80m	18 days	4
Landsat – 4, 5	TM	1982 - 1999	30m, 120m	16 days	6, 1
Landsat – 7	ETM	1999 – present	15m, 30m, 60m	16 days	1, 6, 1
Landsat - 8	OLI	2013 – present	15m, 30m, 100m	16 days	1, 8, 2
SPOT – 1, 2, 3	HRV	1986 – present	10m, 20m	26 days	1, 3
SPOT - 4	HRVIR	1998 – present	10m, 20m	26 days	1, 4
SPOT – 5	Pan MS	2002 - 2015	2.5m - 5m 10m	26 days	2 4
IRS – 1A, 1B	LISS-1 LISS-2	1988 - 1999	73m 36m	4/5 days	4 4
IRS – 1C, 1D	Pan LISS-3	1995 – present	5.8m 23.5m, 70m	4/5 days	1 3,1
Terra	ASTER	1999 – present	15m, 30m, 90m	16 days	3, 6, 5
NOAA/TIROS	AVHRR	1978 – present	1.1 Km	1 day	5
IKONOS	Pan MS	1999 – present	1.0m 4.0m	3 days	1 4
Quick bird	Pan MS	2001 – present	0.61m 2.44m	1-4 days	1 4
RADAR					
ERS – 1, 2		1991 - 2011	30m	1-2 days	C-band
JERS – 1		1992 – 1998	18m	24 days	L-band
RADARSAT – 1		1995 – 2013	10m – 100m	3 days	C-band
ENVISAT		2002 – 2011	30m, 150m, 1Km	35 days	C-band

2.5. Discussion

The advancements in remote sensing technologies have offered improved capabilities for mapping soil erosion. The aim of this current work was to examine the usage and users of remote sensing in soil erosion research by focusing on three aspects of the published material namely i) publication details, ii) geographic information and iii) data usage. The analysis on these three aspects facilitated in identifying trends and gaps in the usage and users of remote sensing.

The application of remote sensing for soil erosion mapping and monitoring has a long history dating back to the 1960s where the first research paper by Jones and Keech (1966) was published. Since then, an increase in the number of publication was observed from 1976 which could be attributed to the launch of the first ever satellite system – Landsat in 1972 (Karale *et al*., 1976; Proffiit, 1983, Frazier *et al*., 1983; Pickup and Nelson, 1984). The launch of Landsat set precedent for soil erosion mapping and monitoring (Taruvinga, 2009). It can be explained that the increase in the number of publications over the years has been attributed to the progression of remote sensing technologies with its capabilities to provide timely and cheaper alternative to mapping and monitoring soil erosion.

In the recent years, literature shows that most studies focused on assessing and mapping gully erosion at catchment and regional scales (Vrieling *et al*., 2007; Igbokwe *et al*., 2008; Ndomba *et al*., 2009; Bouaziz *et al*., 2011; Shruthi *et al*., 2011; Frankl *et al*., 2013, d'Oleire-Oltmanns *et al*., 2014; Le Roux and Sumner, 2012, Mararakanye and Sumner, 2017). This trend shows that remote sensing has made tremendous strides in providing accurate information of soil erosion assessment that has been of benefit to land managers and policy makers as field methods often limit regional scale assessment. Furthermore, this trend is also reflected in the journal categories that have published the reviewed studies. A substantial growth of papers published in strictly specialized remote sensing journals to more interdisciplinary journals was observed from 2006 onwards. Interdisciplinary journals facilitate in knowledge and research dissemination across the diverse research communities (Jacobs and Henderson, 2012), thus this trend indicates that remote sensing technology has become widely accepted across the scientific community.

Moreover, literature shows that remote sensing applications for soil erosion have mostly been applied in the semi-arid regions such as Spain, South Africa and India (Iyer, 1974, Kumar *et al*., 1996; Dwivedi *et al*., 1997; Wessels *et al*., 2004; Le Roux and Sumner, 2012; Seutloali *et* *al*., 2016; Kumar *et al*., 1997) drawing attention to the environmental vulnerability of these regions. Interestingly, the Loess Plateau of China is one of the most severely eroded regions however only 4 studies were identified (Ma *et al*., 2003; Wang *et al*., 2007; Chen *et al*., 2011; Wang *et al*., 2016). Most studies in this region mainly use GIS techniques to model and quantifying soil loss. Similarly, according to the soil degradation world map by Oldeman *et al*. (1991), countries, such as Nigeria, Ethiopia and Sudan are classified as one of the most severely eroded; however, a limited number of studies were identified from these countries (Fadul *et al*., 1999; Igbokwe *et al*., 2008; Tahir *et al*., 2010; Frankl *et al*., 2013; Okereke *et al*., 2012).

It is interesting to note that although remote sensing has been an effective tool used globally, reaching broader scientific domains, the origin of first authors for the published papers shows rather a disproportionate observation. It was observed that authors who are affiliated with European institutions (Tahir *et al*., 2010; Frankl *et al*., 2013; Ranga *et al*., 2015) published studies conducted in developing countries, such as India, Sudan, Ethiopia, Morocco etc. Innovative knowledge is mainly generated in developed countries where research funding is available (Chan and Costa, 2005). For instance, the reviewed studies conducted in the aforementioned developing countries were funded by European foreign institutions such as the Norwegian Research Council (NFR) program from Norway and Erasmus Mundus External Program window 13 from Belgium. According to Chan and Costa (2005) there is a limited capacity for research infrastructure and knowledge in developing countries, resulting in a shortage of scientific output and further under-development, further widening the North and South knowledge gap. Karlson and Ostwald (2016) argue that joint efforts to increase the capacity of local researchers and institutions for conducting research using the new generation of remote sensing datasets are necessary to achieve this objective.

Moreover, literature also shows that a wide range of remote sensing systems have been used at different scales for mapping and monitoring soil erosion. While high resolution sensors are important for the accurate detection of erosion features, the use of these sensors is restricted by availability and cost (Hoque *et al*., 2017). Numerous studies have used medium resolution Landsat sensors, due to its open access archival data and spectral resolution, offering the potential for soil erosion monitoring (Singh, 1977; Metternicht and Fermont, 1998; Sujatha *et al*., 2000; Okereke *et al*., 2012; Dube *et al*., 2017). Although these studies highlight the incapability of Landsat to detect small erosion features due to its coarse – medium resolution, nonetheless, Landsat offers the potential to map soil erosion at regional scales with reasonable accuracy due to its large swath-width of 185km. On the other hand, sensors, such as Quickbird, IKONOS and Worldview provide the ability to accurately map fine erosion features due to their fine spatial resolution. However it is not surprising that only a limited number of studies have used these sensors as they are not freely available and access to these datasets remains a challenge in resource constrained countries (Meusburger *et al*., 2010; Shruthi *et al*., 2011; d'Oleire-Oltmanns *et al*., 2014; Uchida 2015). Similarly, it was observed that a limited number of studies have used radar datasets for soil erosion mapping thus far (Metternicht and Fermont, 1998; Navone and Palacín, 2004) and this opens up possibilities to evaluate the potential of Sentinel-1 products.

The review analysis further showed that traditional approaches, such as the visual interpretation and the MLC have remained popular over the years in detecting and mapping soil erosion (Symeonakis *et al*., 2007; Vrieling *et al*., 2007; Le Roux and Sumner, 2012). The MLC however suffers from drawbacks that include its limitation in solving complex classes that are not normally distributed (Sepuru and Dube, 2017). By contrast, the increase of high-resolution sensors has facilitated a shift from traditional pixel-based classification to object-based image analysis (OBIA) methods (e.g. Shruthi *et al*., 2011; d'Oleire-Oltmanns *et al*., 2014; Mayr *et al*., 2016). This presenting a new and accurate approach for soil erosion mapping owing to its ability to involve analysing the characteristics of an object based on its location, size, shape and spectral properties (Bishop *et al*., 2012).

2.6. A way forward

There is significant progress in the detection and mapping of soil erosion using remotely sensed data. This review shows a considerable increase of remote sensing usage and users for soil erosion analysis since the launch of Landsat series data dating back in 1972. Several studies have used Landsat for soil erosion mapping due to its archival data and open access policy, which makes it ideal for long term soil erosion monitoring. The improving capacity and availability of remotely sensed data is promising for soil erosion especially gully erosion mapping at regional scale. A number of studies confirm the effectiveness of medium resolution sensors such as that of Landsat in mapping soil erosion at regional scale. For instance, the recently launched Landsat 8 sensor offers improved spectral and radiometric resolution that is ideal for regional and local soil erosion mapping (e.g. Phinzi and Ngetar, 2017; Dube *et al*., 2017; Seutloali *et al*., 2017). In addition, powerful machine learning algorithms, such as the SVM have been equally valuable for soil erosion mapping. These algorithms can offer improved classification accuracies for soil erosion mapping, even more so with medium-coarse resolution satellites (e.g. Taruvinga, 2009; Bouzazi *et al*., 2011; Chen *et al*., 2011).

On the other hand, fine resolution satellites, such as the likes of SPOT, QuickBird and IKONOS offer tremendous results for soil erosion detection and have been recommended by several studies for accurate soil erosion mapping owing to their high quality data. These satellites however present limitations for large-scale mapping due to high data acquisition costs and are prohibitive for developing countries (Vrieling *et al*., 2008). Besides, Sepuru and Dube (2017) argue that while SPOT is relatively cheaper than IKONOS and QuickBird, these satellites are still further limited by their low spectral sampling abilities.

Nonetheless, the recently launched and freely available Sentinel 2 sensor is now the new leader in spatial resolutions amongst multispectral imagery, with a spatial resolution of 10m, a 5-day revisit cycle coverage and 12 multispectral bands. The application of Sentinel 2 in land cover mapping has been demonstrated to provide information on environmental management. Studies that have applied the Sentinel 2 imagery have observed improved results for land cover mapping. For example, Buchholz *et al*. (2012) assessed the effectiveness of Sentinel-2 data for land cover mapping and compared its performance with Landsat-5 TM and SPOT 5-HRG imagery. The study further used the MLC and SVM to assess the discrimination capabilities offered by different features and revealed promising results by Sentinel-2. Sentinel 2 therefore offers a great potential for soil erosion mapping mainly for developing countries which are often constrained by high data acquisition costs (Sepuru and Dube, 2018).

While several studies have demonstrated the ability of medium resolution satellite sensors to discriminate soil erosion features from other land cover types, there is a paucity of multisource image fusion methods for soil erosion studies (Chen *et al*., 2011). In addition, the review also identified insufficient work of the application of active microwave radar data fused with optical multispectral data for soil erosion mapping. Therefore, it is necessary for future studies to explore the potential of robust classifiers such as the SVM, OBIA and recently launched Sentinel products for improving the detection and accuracy of soil erosion mapping.

2.7. Conclusion

- The use of remote sensing for soil erosion analysis has gradually increased from 1966 to present time, reaching 104 peer-reviewed articles; noting the largest increase in the last 11 years.
- Remote sensing has become widely accepted as an effective tool for soil erosion analysis as reflected in the range of interdisciplinary scientific journals.
- The geographical distribution of the application of remote sensing for soil erosion shows that research is mainly conducted in semi-arid regions (i.e. Spain, South Africa and India) which could possibly be driven by the prevailing environmental problems.
- European affiliated authors generally lead research conducted in developing countries. The review further revealed a low representation of African lead authors.

CHAPTER THREE

Assessing the potential of Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies in a communal grazing landscape

This chapter is based on:

Makaya, N. P., Mutanga, O., Kiala, Z. S., Dube, T. and Seutloali, K. E. 2018. Assessing the potential of Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies in a communal grazing landscape. *Physics and Chemistry of the Earth*. 1-26. JPCE_2018_114. (Under review).

Abstract

In this study, we evaluate the potential of the recently launched Sentinel-2 MSI multispectral sensor in mapping the spatial distribution of gullies in Okhombe valley, KwaZulu-Natal, South Africa. The study further investigates possible environmental factors that contribute towards gully initiation and development. Analysis was done using a robust machine learning algorithm: Support Vector Machine (SVM). Additionally, possible environmental factors (i.e. slope steepness, percent vegetation cover, Topographic Wetness Index and Stream Power Index) that could have an influence on the extent of the gullies were also derived. An overall land cover classification of 94% was achieved, while the overall classification accuracy for gullies was 77%. All 10 Sentinel-2 spectral bands were selected as the ideal bands in discriminating gullies from other land cover types. Additionally, the findings of the study indicate that there is no significant difference between the environmental variables across different gullies volumes. The findings of the study indicated that all the measured variables have a weak influence on the volume of soil loss (i.e. Slope (R^2 = 0.02); Vegetation cover (R^2 = 0.01); TWI (R^2 = 0.11) and SPI (R^2 =0.02) despite an observable trend of influence. Overall, the findings of the study demonstrate the importance of using the free and readily available multispectral Sentinel-2 MSI data in conjunction with robust non-parametric Support Vector Machine classifier in mapping the spatial distribution of gullies.

Key Words: Gully erosion, satellite imagery, communal landscape, soil loss

3.1. Introduction

Gully erosion is a major land degradation problem that threatens both land and water resource management in arid and semi-arid regions across the globe (Kakembo *et al*., 2009; Rahmati *et al*., 2017). Gullies are commonly defined by their channel depth, which can range from 0.5 to 30 m and often develop into a network of active gullies that contribute a significant amount of sediment yield in catchments (America, 2001; Le Roux and Sumner, 2012). Gullies predominantly occur in dry regions and are exacerbated by rapid land use change due to demographic, economic and grazing and agricultural pressure (Poesen *et al*., 2003; Chaplot *et al*., 2005). This consequently results in irreversible environmental impacts, such as soil degradation, high volumes of sediment yield, reduction of both water quality and quantity in rivers and reservoirs, damage to agricultural fields and infrastructure (Takken *et al*., 2008; Dewitte *et al*., 2015). For instance, Luk (1997) reported that 85% of sediment yield in a reservoir were accounted by gullies in a 0.73 Km^2 catchment, Southern China. Similarly, Verstraeten *et al*. (2003) conducted a survey which reported that gullies increased sediment yield within the catchments of 22 Spanish reservoirs observing mean specific sediment yield of 9.61 tons ha^{-1} $year^{-1}$ (n=7).

Researchers have shown a large interest on gully erosion, due to its related offsite impacts which raise concern for water resource management at catchment scales (Wasson *et al*., 2002; Valentin *et al*., 2005; Poesen, 2011; Mararakanye and Le Roux, 2012). While many studies have addressed gully erosion at local to catchment scale, there is a need for a comprehensive understanding of the spatial distribution and driving factors on gully erosion at regional scale. Therefore, accurate and frequent monitoring of gully erosion is necessary for the implementation of erosion control measures and prioritization strategies for the allocation of scarce conservation resources and policy development (Vrieling, 2006; Seutloali *et al*., 2016). However, the acquisition of accurate and up-to-date spatial information of gully affected areas remains a challenge, especially in sub-Saharan Africa where data availability and quality is often poor for regional scale mapping (Vrieling *et al*., 2006; Dube *et al*., 2017). Additionally, acquiring accurate spatial data is further hampered by the use of traditional techniques, such as digitizing and field surveys amongst others (Dube *et al*., 2017). Gullies have been traditionally mapped using visual interpretation of aerial photos or satellite imagery and this methods are spatially constrained, time-consuming, labour-intensive and costly at regional scale (Vrieling, 2006; Shruthi *et al*., 2011; Frankl *et al*., 2013). The development in sensor technology and techniques in the recent years has seen an improvement in the accuracy detection of gullies at a regional scale.

Previous studies have demonstrated the effectiveness of remote sensing in enhancing an understanding of the scale and level of soil erosion at regional scale, a previously challenging task from conventional methods (Kumar *et al*., 1996; Zinck *et al*., 2001; Manyatsi and Ntshangase, 2008; Liberti *et al*., 2009; Seutloali *et al*., 2016, Phinzi and Ngetar, 2017). For example, Igbokwe *et al*. (2008) successfully mapped gully erosion in South-eastern Nigeria, using Landsat ETM, Nigeria-sat1 and SPOT 5 and SRTM dataset. While Bouaziz *et al*. (2011) mapped gully erosion in the Main Ethiopian Raft using ASTER, achieving a maximum overall accuracy of 89%. Similarly, Mararakanye and Le Roux (2012) mapped gully erosion at national scale in South Africa using SPOT 5 and achieved an overall accuracy of 90%.

A recent trend in the use of high spatial resolution sensors, such as IKONOs, QuickBird, and GeoEye has seen a change from traditional pixel-based to object-based techniques (e.g. Shruthi *et al*., 2011; Ranga *et al*., 2016; Mayr *et al*., 2016). Although these sensors provide a high spatial resolution, image acquisition is costly and limited to both small area coverage and spectral bands (Taruvinga, 2009). These pose a limitation for large scale mapping and monitoring of gully erosion in resource constrained regions, such as southern Africa (Seutloali *et al*., 2016). Nonetheless, freely available medium resolution images, such as Landsat have been widely used successfully in soil erosion research owing to their cost effective and temporal resolution which facilitates a large scale monitoring of soil erosion. Moreover, the recently launched and freely available Sentinel-2 MSI sensor provides a more improved spatial resolution (i.e. resolution of 10m, 5-day revisit cycle coverage and 12 multispectral bands amongst multispectral imagery characterised by a spatial. Studies that have applied Sentinel-2 imagery have observed improved results for land cover mapping (Forkuor *et al*., 2018). The spatial and radiometric characteristics of Sentinel-2 sensor make it ideal for mapping individual gullies at region scale. It is therefore perceived that the use of this sensor can help soil erosion monitoring in data scarce environments – a previously challenging task with broadband sensors. The current study therefore a) evaluates the potential of Sentine-2 MSI in discriminating gullies from other land cover types using semi-automatic SVM algorithm; and b) investigates possible environmental variables that contribute to gully initiation and development in Okhombe valley, KwaZulu-Natal, South Africa.

3.2. Materials and Methods

3.2.1. Description of Study Area

Okhombe valley is a communal grazing land located in the upper uThukela catchment in KwaZulu-Natal, South Africa. The study site has an area of 59.89 Km^2 (28°42' S; 29°05 'E) (Fig. 3.1). The valley is located within 10 to 20 km of the north-eastern border of Lesotho and is characterized by steep topography, with an elevation ranging from 1200 - 1800m above sea level. Grasslands are the main dominant vegetation cover in the area, with a few scattered patches of woody vegetation and shrubs. Okhombe soils are red and yellow, freely drained, structure-less, highly leached and severely eroded and this is caused by the high rainfall that typically falls between October and March (Macavicar, 1977; Schulze, 1997; Everson *et al*., 2007). The early 1960s marked a significant change in agriculture which transformed the settlement distribution of the Okhombe catchment, resulting in the removal of people to one of six closer settlements at the foot slopes (von Maltitz and Evans, 1998). Communal grazing land was designated along the steep slopes plateaux while the valley floor was designated for cultivation (Sonneveld *et al*., 2005). The grazing camps that were designed to accommodate different types of cattle are no longer being managed and this has resulted in the lack of cattle movement control (Sonneveld *et al*., 2005). Furthermore, the lack of security and theft has resulted in cattle being kept near the homesteads and are daily moved up and down the slopes (Sonnoveld *et al*., 2005). This has caused great concern of soil erosion due to the trampling effects.

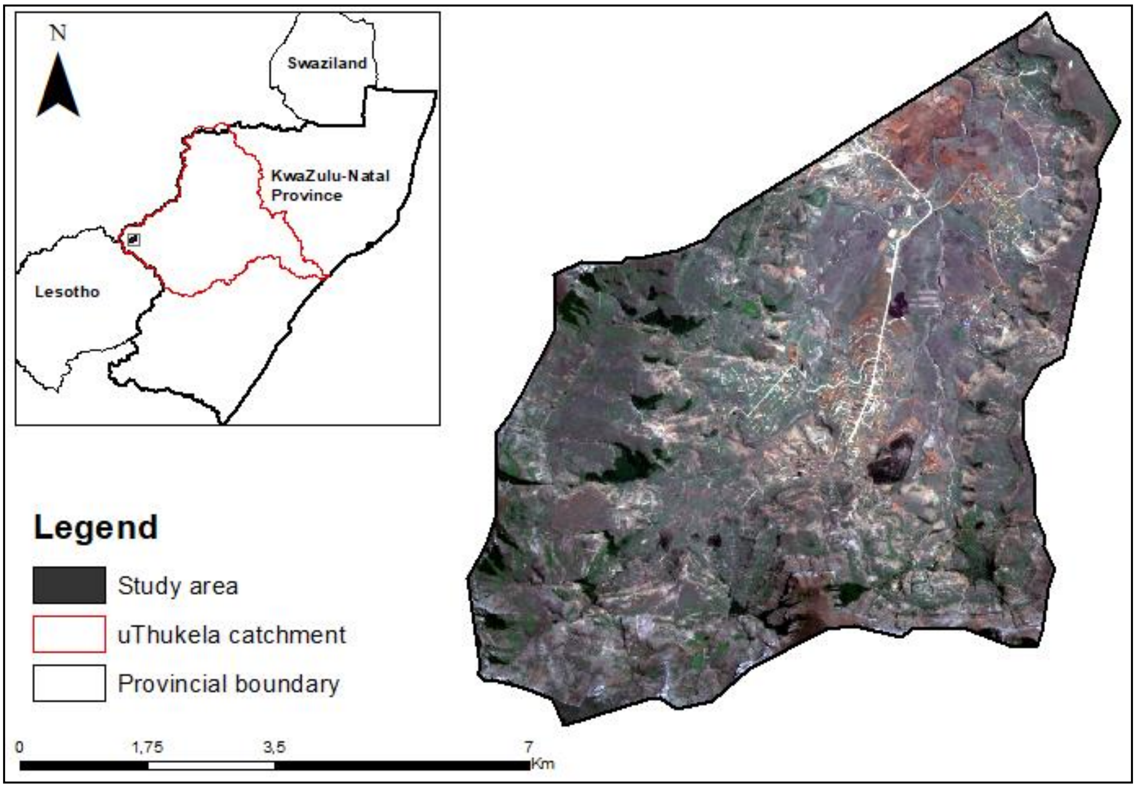

Fig. 3. 1: Location of Okhombe in the uThukela catchment, KwaZulu-Natal, South Africa Study Area map

3.2.2. Filed data collection

Field data were collected from the 31st of October to the 4th of November 2016 and from the 5th to the 9th of December 2016. Data collection was done using a differentially corrected Trimble GeoXT handheld Global Positioning System (GPS) receiver, with sub-meter accuracy. In addition, the ground truth data for gully locations and other Land Use/Land Cover (LULC) classes, such as grassland, forest, shrubland, settlement and bare soil were collected. Although random sampling is considered the most favourable sampling technique, due to its ability to remove bias, it was not appropriate specifically for the objective of the study as gullies are not homogenously distributed across the landscape. A purposive sampling technique was therefore used to identify gully locations. A sample of 83 gullies was recorded. Gully dimensions i.e. length, width and depth were estimated using a surveyor's tape and ranging poles for the estimation of gully volume, which is equivalent to the volume of soil lost (shown in Fig. 3.2) (Jungerius *et al*., 2002; Seutloali *et al*., 2015). Gully dimensions were measured at every 10m intervals and then averaged to account for change in topography at the cross section as well as the sensor spatial resolution. Gully depth was measured at the maximum deepest point of the gully coinciding with the 10m intervals. The gully volume was estimated using the formula expressed in equation 1.

$$V = L \times [(Wt + Wb) / 2] \times D \quad (1)$$

Where: V is the volume in cubic metres; L is the total length in metres; Wt is the average top width in metres; Wb is the average bottom width in metres; D is the average depth measured in metres.

Percentage vegetation cover was visually estimated, using the method by Daubenmire (1959). 10x10m plots were demarcated to estimate the upslope percentage vegetation cover coinciding with the identified gullies. This is of the assumption that the presence of gully erosion is possibly attributed to the drainage area and amount of vegetation cover surrounding it. Vegetation cover plays a pivotal role in protecting the soil surface against erosion (Vrieling, 2006). It is defined as the fraction or percentage of the ground surface covered by vegetation (Purevdorj *et al*., 1998).

Fig. 3. 2: Photographs showing some of the gullies identified in the Okhombe valley (October 2016)

3.2.3. Topographic variables

Various major topographic variables contribute to gully development (Kheir *et al*., 2007). Topography plays a pivotal role in concentrating water flow and Mararakanye (2016) argues that the role of topographic variables has not been widely reported in South Africa. A 10m Digital Elevation Model (DEM) acquired online from the web link (http://www.csg.dla.gov.za) was processed in a GIS environment, using the spatial analyst tools to generate slope gradient, Topographic Wetness Index (TWI) and Stream Power Index (SPI). The slope gradient was calculated in degrees using the formula expressed in equation 2.

$$\text{SLOPEDEG} = \text{RADDEG}\,(\text{Atan}(\text{SLOPEPCT}/100)) \qquad (2)$$

Where SLOPEDEG is the slope gradient in degrees, RADDEG is the function of converting radians to degrees and Atan is a mathematical function used in the conversion process (Seutloali *et al*., 2016).

The Topographic Wetness Index (TWI) is a function of the specific catchment area and slope gradient of the landscape (Feng and Bajcsy 2005) and was calculated using the formula expressed in equation 3.

$$\text{TWI} = \ln\,(A_s/\tan\beta) \qquad (3)$$

Where A_s is the specific catchment area and β is the upslope gradient in degrees (Tagil and Jenness, 2008).

The Stream Power Index (SPI) on the other hand indicates an estimation of the erosive power of the terrain and was calculated using the formula expressed in equation 4.

$$\text{SPI} = A_s \tan\beta \qquad (4)$$

Where A_s is the specific catchment areas and β is the local slope (Wilson and Gallant, 2000).

3.2.4. Image acquisition and processing

A cloud-free Sentinel-2 MSI imagery of January 2016 was freely acquired from the European Space Agency (ESA) online catalogue (https://scihub.copernicus.eu/). Table 3.1 provides an overview of the characteristics of the Sentinel-2 data used in this study ranging from the visible through the near-infrared (NIR): and red edge to shortwave infrared (SWIR) at 10, 20 and 60m spatial resolution. Band 1 (coastal aerosol), Band 9 (water vapour) and Band 10 (cirrus), acquired at 60m spatial resolution are designed mainly for detecting atmospheric features and were therefore not included in the analysis (Drusch *et al*., 2012). The imagery was atmospherically corrected, using the Sen2Cor atmospheric correction toolbox – an inbuilt algorithm within the Sentinel Applications Platform (SNAP) version 5.0. All 10 bands of varying spatial resolutions were further resampled to 10m to ensure that the pixel size of the image corresponds with the identified gullies. The imagery was then used for the classification of gullies using the ground truth data.

Table 3. 1: Sentinel-2 MSI Spectral and Spatial resolutions.

Spectral Bands	Centre (nm)	Spatial Resolution (m)
Band 1 – Coastal aerosol	443	60
Band 2 – Blue	490	10
Band 3 – Green	560	10
Band 4 – Red	665	10
Band 5 – Vegetation Red Edge	705	20
Band 6 - Vegetation Red Edge	740	20
Band 7 - Vegetation Red Edge	783	20
Band 8 – NIR	842	10
Band 8a – Narrow NIR	865	20
Band 9 – Water vapor	945	60
Band 10 – SWIR	1375	60
Band 11 – SWIR	1375	20
Band 12 - SWIR	2190	20

3.3. Data Analysis

Sentinel-2 MSI imagery was used to discriminate gullies from other land cover types in uThukela Catchment. The SVM algorithm was used to classify the images. The SVM was chosen, due to its ability to perform a robust discrimination of complex land cover classes, such as gullies and has been previously used successfully to classify gullies (Taruvinga, 2009; Le Roux and Sumner, 2012). The algorithm is regarded as a non-parametric machine learning algorithm first introduced by Boser *et al*. (1992). The SVM determines the separation of decision boundaries between different classes by directly searching for suitable boundaries (Huang *et al*., 2002). The non-parametric and "one class classification" (i.e. when one class is of interest) characteristic sets the SVM apart from the rest of the conventional classifiers (Sanchez-Hernandez *et al*., 2007) and thus offers a potential for mapping individual medium-sized gullies in South Africa. The SVM classification was performed; using spectral reflectance signatures of each land cover type on the Sentinel-2 imagery which was used to train the classification of the imagery. The data was then divided into 70% and 30% training and validation, respectively, for the classification procedure (Adelabu *et al*., 2013; Sibanda *et al*., 2015).

3.3.1. Image classification optimization

The Recursive Feature Elimination (RFE) and hyper-parameter tuning algorithm was used for the Support Vector Machine model optimization. The RFE selection technique ranks features based on the measure of their importance where feature importance is measured and the less important feature is removed thereby speeding the process (Granitto *et al*., 2006). This is an essential process that determines the best parameters for the highest classification accuracy (Abdel-Rahman *et al*., 2014). Spectral band importance rankings were generated, using a grid based and tenfold cross validation feature selection process (Waske *et al*., 2009). A forward selection method was then achieved to select the least number of the spectral bands that produced the highest overall classification accuracy, generating a new model based on the highest ranked bands (Kohavi and John, 1997). The use of feature selection allows for a reduced data training time while improving classification accuracy concurrently. Hyper parameter tuning was performed on the model created from the selected bands using the Grid-search approach.

3.3.2. Accuracy assessment

The validity and reliability of the classification results produced by the SVM-REF model was assessed using the Confusion Matrix. The classification accuracy assessment is determined by a cross-tabulation method on the contingency table where each class label is evaluated against the corresponding ground data (Foody and Mathur, 2004). A confusion matrix was produced to measure the producer accuracy (PA), user accuracy (UA) and overall accuracy (OA) between the classification results and ground truth data.

3.3.3. Statistical analysis

To determine differences in gully volume (i.e. estimated soil loss) and within each environmental factor, class ranges were applied as shown in Table 3.2. These variables were categorised into three classes based on observations that informed the influence of gully development (Le Roux and Sumner, 2012). Simple linear regression was utilised to determine, as well as evaluate the relationship between the environmental factors and gully volumes and hence the coefficients of determination (R^2) were reported. The One-way analysis of variance (ANOVA) at 95% confidence level ($P < 0.05$) was then conducted to determine whether there were any significant differences between environmental factors (i.e. vegetation cover, slope, topographic wetness index (TWI) and Stream Power Index (SPI)) and the estimated soil loss.

Table 3. 2: Classes ranges of environmental variables.

Biophysical variable	**Class Name**	**Class Range**
Slope (°)	Flat - Gentle	<11
	Gentle – Moderate	11-17
	Steep – Very Steep	>17
Vegetation cover (%)	Bare - Low	<38
	Low – Moderate	38-48
	Moderate - High	>48
Topographic Wetness Index (TWI)	Low	<3.5
	Moderate	3.5-15.5
	High	>15.5
Stream Power Index (SPI)	Low	<0.19
	Moderate	0.20-0.49
	High	>0.49

3.4. Results

3.4.1. Gully spectral profile

Fig. 3.3 illustrates the average spectral response profile of individual gullies and two other land cover classes (i.e. grasslands and bare soil) that have been observed to be similar to the gullies. It can be observed that the general reflectance of gullies is low compared to bare soil, which remained relatively high, while there is a similarity of signatures between gullies and grassland for Band 8 and Band 8A.

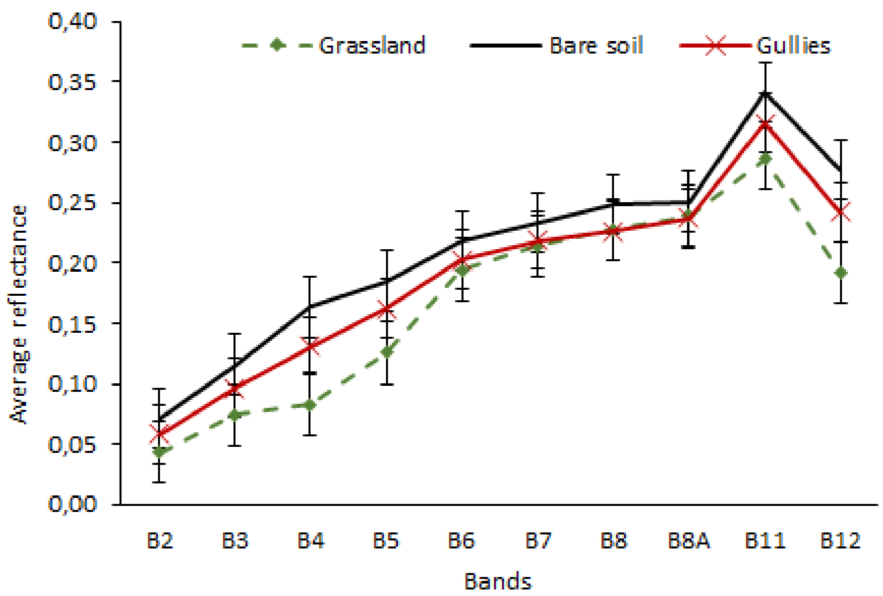

Fig. 3. 3: Spectral signatures of gullies, grassland and bare soil derived from Sentinel-2 MSI imagery (error bars signifying level of separability).

3.4.2. Major land cover types

Land cover classification results obtained using Sentinel-2 MSI spectral bands as an independent dataset are shown in Table 3.3. The results indicate that the use of the freely available medium resolution Sentinel-2 MSI spectral bands produced good classification results, achieving an OA of 94%. Of all the five classes, shrubland achieved the highest producer accuracy of 100% while forest achieved the highest user accuracy of 100%. Moreover, the Senitnel-2 MSI imagery yielded good classification results in discriminating gullies from other land cover types producing a Producer Accuracy of 78%, User Accuracy of 76% and an Overall Accuracy of 77%. Fig. 3.4 (a) illustrates land cover types within the catchment while Fig. 3.4 (b) illustrates the widespread spatial distribution of gullies within the catchment. It is important to note that some of the areas affected by gullies include more than one gully, especially where several small gullies are located in close proximity with each other often forming a network. It can be observed that areas affected by gullies are largely distributed across the valley.

Table 3. 3: Sentinel-2 MSI accuracies (%) for land cover classes including gully location.

Land Cover type	**Producer Accuracy (%)**	**User Accuracy (%)**	**Overall Accuracy (%)**
Grassland	94	95	95
Forest	93	100	96
Shrubs	100	99	99
Bare land	95	95	95
Gully location	78	76	77
Burnt grass	90	86	93
Overall Accuracy (%)	94		

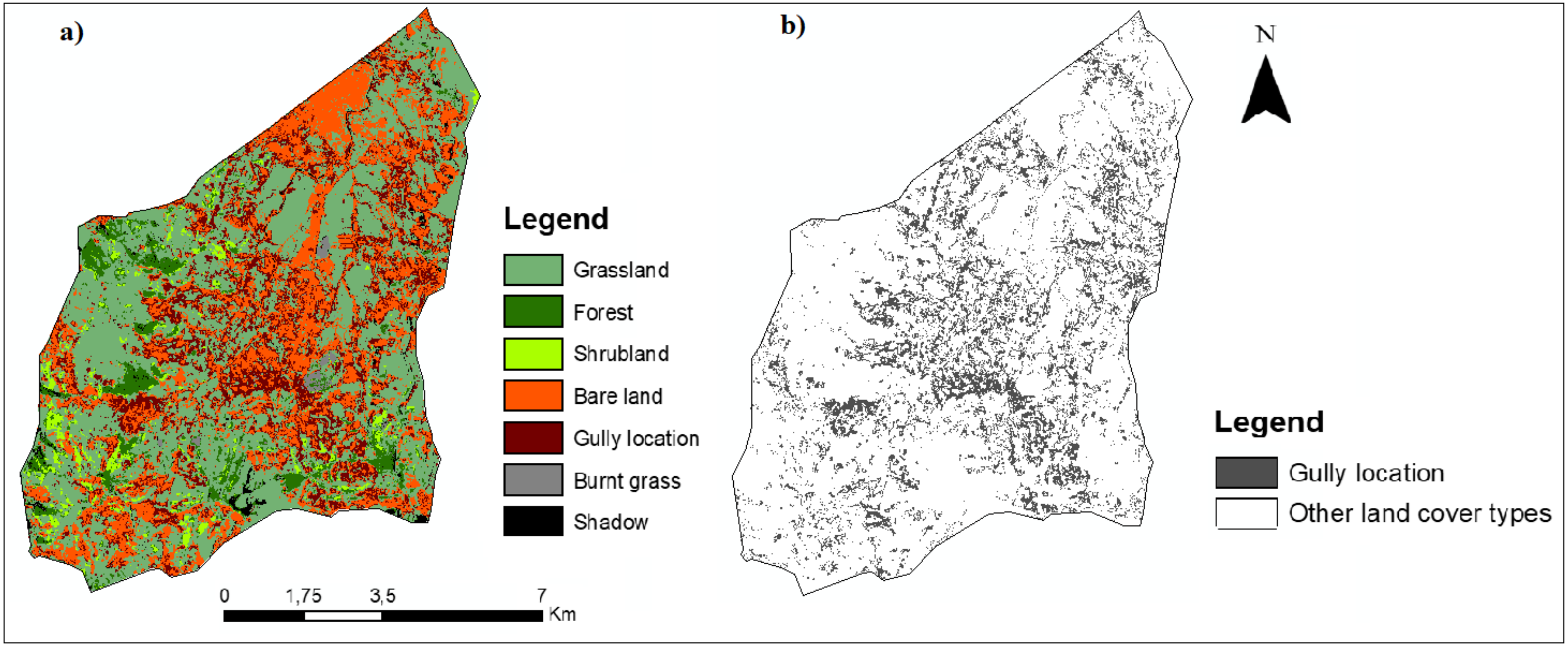

Fig. 3. 4: Derived gully maps in relation with surrounding land cover types in uThukela catchment where a) shows the derived land cover classification and b) shows the derived gully distribution.

3.4.3. Evaluating the relationship between gully volumes and environmental variables

Fig. 3.5 illustrates the spatial distribution of the possible environmental variables that influence gully development (i.e. Slope gradient, Vegetation cover, TWI and SPI). To achieve a clearer understanding, the possible environmental variables were classified into three categories as shown in Fig. 3.5. The slope steepness within the catchment ranges from flat to very steep (i.e. 3°to 60°). The estimated percent vegetation cover within the catchment ranges from 7% to 90% which has been classified as fairly bare to high percentage vegetation cover as shown in Fig. 3.5. The majority of gully locations were mainly identified in areas with fairly bare to low vegetation cover, while a few gullies were identified in areas with high vegetation. TWI values within the catchment range from -42 to 86, while the SPI values within the catchment range from approximately -3 to 2.

Fig. 3.6 illustrates a summary of the relationship between the estimated mean gully volumes and the classes of possible environmental variables (i.e. Slope, vegetation cover, TWI and SPI) for gully development. The results indicate that higher mean gully volumes of about 530 m^3 were associated with flat to gentle slope gradients (slopes less than 11°) while the very steep gradients had lower mean gully volume of about 212 m^3. In addition, higher mean gully volumes of about 450 m^3 were associated with low vegetation cover (vegetation cover less than 38%) while moderate to high vegetation cover (greater than 50%) were associated with lower mean gully volumes of 268 m^3. Similarly, higher mean gully volumes of 578 m^3 were also associated with high TWI values (greater than 16.30) indicating possible gully development on the high zones of saturation on fairly flat area. Similarly, higher SPI values (greater than 0.51) were associated with higher gully volumes of about 329 m^3.

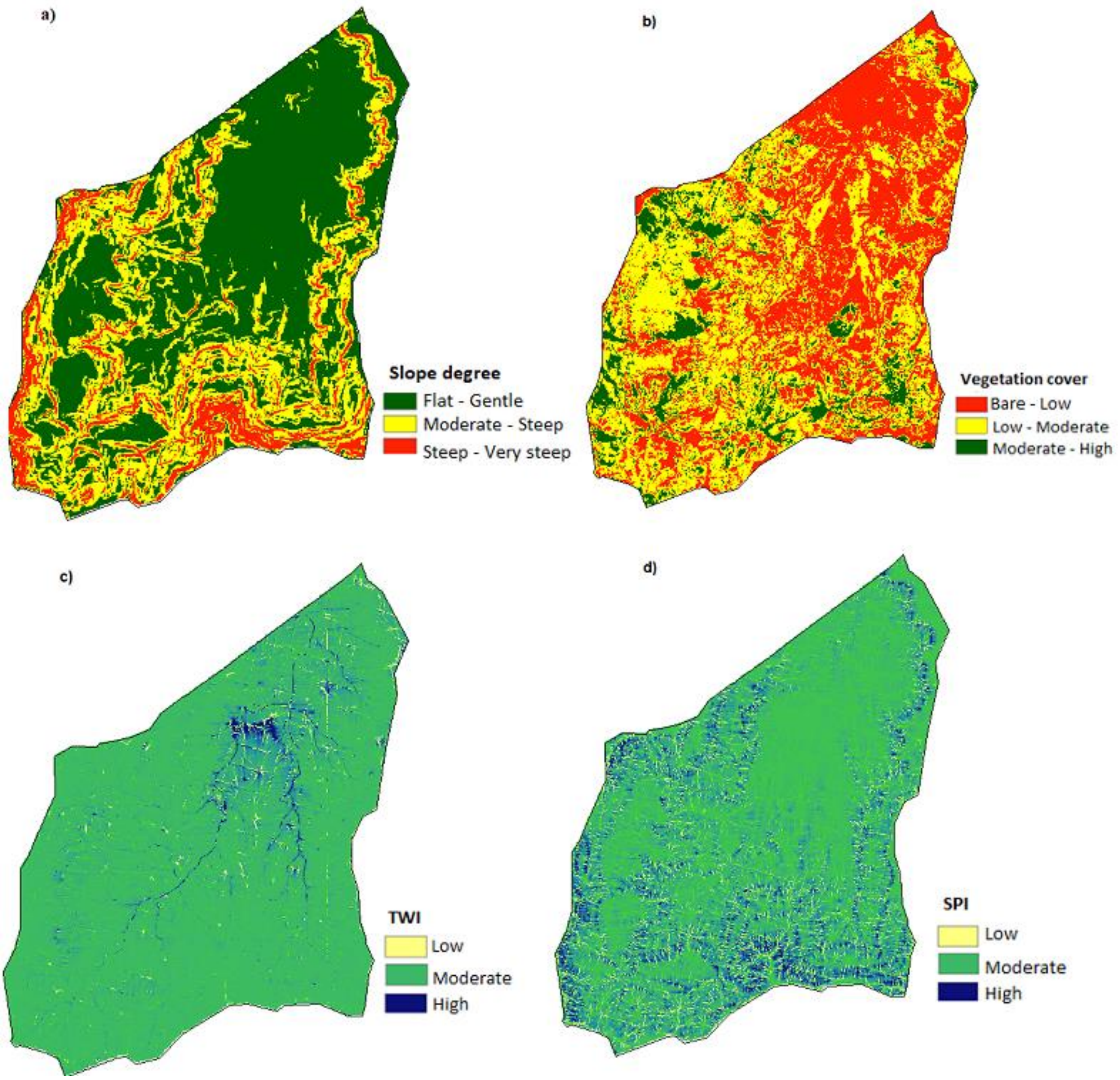

Fig. 3. 5: The spatial distribution of (a) Slope; (b) vegetation cover; (c) TWI; and (d) SPI) contributing to gully development.

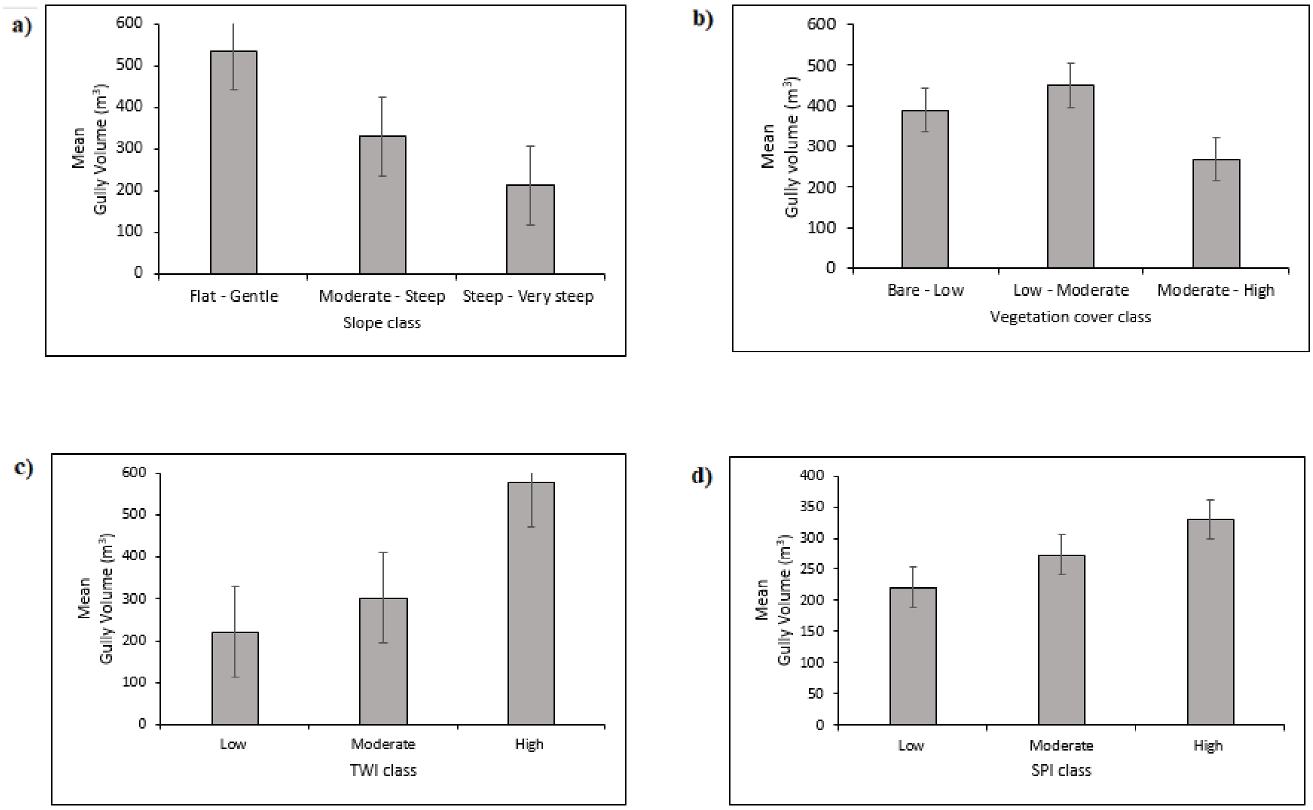

Fig. 3. 6: The relationship between mean gully volume and (a) slope; (b) vegetation cover; (c) TWI; and (d) SPI.

Fig. 3.7 illustrates the relationship between mean gully volume and environmental variables. Although there seems to be a discernible pattern of the possible environmental variables and gully volumes, however based on the 95% confidence interval, the results show that none of the environmental variables (i.e. slope, percent vegetation cover, TWI and SPI) had a significant influence on gully volumes (ANOVA; $F(0.048) = 0.0953$, $p = 0.05$; $F(0.695) = 0.0502$, $p = 0.05$); $F(0.702) = 0.499$, $p = 0.05$); ($F(0.455) = 0.0636$, $p = 0.05$). Additionally, Fig. 3.7 further depicts the correlation between the estimated gully volumes and environmental factors (i.e. slope, percent vegetation cover, TWI and SPI). The estimated gully volumes had weak correlations with slope ($R2 = 0.02$), percent vegetation cover ($R2 = 0.01$) and SPI ($R2 = 0.02$) respectively. TWI showed a slightly higher positive correlation ($R2 = 0.11$) as compared to the other variables.

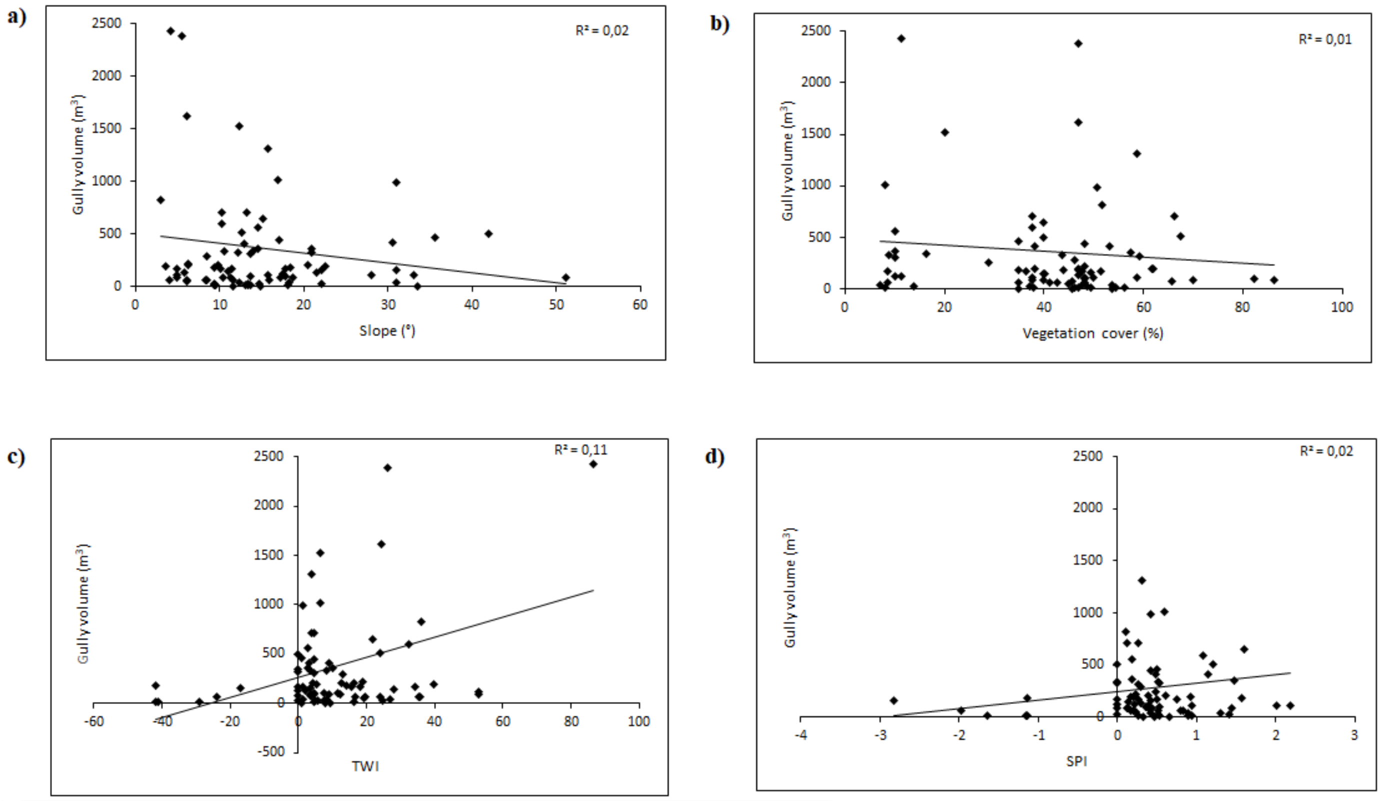

Fig. 3. 7: Relationship between the estimated gully volume (m^3) and a) slope; b) percent vegetation cover; c) TWI and d) SPI.

3.5. Discussion

The recent proliferation of gully erosion research and advances in remote sensing technologies have facilitated in evaluating cheaper methods to provide accurate and timely spatial data for a better understanding of land degradation at catchment scale. Accurate identification of areas affected by gully erosion is paramount for effective soil and water resource management strategies. The current study sought to i) explore the feasibility of the recently launched Sentinel-2 MSI sensor in discriminating and mapping the spatial distribution and extent of gully erosion in a communal grazing landscape and ii) determine the environmental variables that could possibly explain the spatial variation of the gully locations and volumes. The results of this study showed the ability of the newly-launched Sentinel-2 MSI in detecting and mapping individual gullies with an overall classification accuracy of 77%. Standard spectral bands of the Sentinel-2 MSI sensor were used to accurately discriminate gullies from other land cover types.

The observed performance of the Sentinel-2 MSI in the overall classification is mainly attributed to the presence of more spectral bands, improving the spectral separability of gullies (e.g. Sepuru and Dube, 2018). In this study, all 10 spectral bands were found to be valuable in providing information on spectral separability between gullies and other land cover types. This observation indicates the advantage of higher spectral resolution offered by Sentinel-2 for land cover mapping. For instance, in a study by Sepuru and Dube (2018) Sentinel-2 MSI and Landsat 8 OLI were compared in discriminating eroded surfaces from other land cover types. The study found Sentinel-2 MSI bands located in the NIR (0.785–0.900 μm), red edge (0.698–0.785 μm) and SWIR (1.565–2.280 μm) regions to be the most optimal for discriminating degraded soils from other land cover types. The study further found that the lack of information of the red edge band in Landsat 8 OLI could possibly explain the unsatisfactory results when compared to Sentinel-2 MSI. The red edge bands have been proven to improve classification accuracy where studies by Korhonen, Packalen and Rautiainen (2017) and Forkuor *et al*., (2018) confirmed that the absence of red edge bands in most multispectral sensors becomes a disadvantage for the potential mapping of Land Use/land Cover.

The classification results of the mapped gullies drew attention to the spectral complexity of gullies and the distinction with its surroundings which often pose a challenge to the classification technique (e.g. King *et al*., 2005; Servenay and Prat, 2003; Vrieling *et al*., 2007; Torkashvand and Alipour, 2009). For instance, difficulties were faced when trying to discriminate the gullies between natural river bed, gullies between landslides, gullies with vegetation cover, gullies embedded in bare soil and other forms of erosion such as sheet and rill which might have resulted in mixed pixels, thereby reducing classification accuracy. The low spectral reflectance of the gullies in the visible regions could possibly be attributed to the presence of vegetation within the gullies, similarity between gullies and river bed, as well as gully depth. These findings are similar to that of Liberti *et al*. (2009) who used supervised classification to map eroded areas and found that there was low spectral separability from RGB band combinations of Landsat imagery with high levels of misclassification between river bed and eroded areas.

Furthermore, a study by Taruvinga (2009) revealed that the classification process is affected by spectral reflectance of vegetation which differs with wavelength and also by the plant leaves pigment that strongly absorb red and blue wavelengths but reflect green wavelengths. Moreover, since a significant portion of gullies is bare soil, the low spectral reflectance can be attributed to moisture content, organic matter content, texture, structure and iron oxide content (Aggarwal, 2004; Vrieling *et al*., 2005), as well as the shadow factor caused by the gully depth and the irregular surface, trapping incoming light thereby reducing reflectance (Metternicht and Zinck, 1998). Nonetheless, the SVM algorithm proved to be a good method for discriminating gullies from other land cover types in the study area despite challenges of pixel mixing and given the size of the gullies.

The results of this study have further shown that gully development varies with different environmental factors (i.e. slope, vegetation cover, TWI and SPI). Although no statistically significant differences were found between gully volumes (i.e. soil loss) for different the environmental variables, a trend is observable. Studies around the world report that gully erosion mainly occurs on steep slopes; however the results of this study indicate that gullies with the associated high soil loss occur on gentle slopes. These findings are supported by Kakembo *et al*. (2009); Le Roux and Sumner (2012); Manjoro *et al*. (2012) and Seutloali *et al*. (2016) who also found that gullies in South Africa mainly occur on gentle slopes of less than 10°. This was attributed to the concentration of overland flow on gentle slopes. Although this study did not assess the nature of soils, another plausible reason for gully initiation occurring on gentle slopes could be the dispersive nature of the soils in the area. It is highly likely that gully initiation is influenced by duplex soils. The study by Sonnovel *et al*. (2005) confirmed that gully initiation in Okhombe is caused by strong textural breaks at around 20 cm depth with an increase in clay of 10 per cent which result in soil pipes and tunnels. Sonnoveld *et al*. (2005) observed many signs of subsurface water seepage in the gully sidewalls at 20cm depth and concluded that soil piping is likely the cause of gully initiation in the study area.

Moreover, studies have reported the interdependence of land use change and low vegetation cover as drivers of gully development (e.g. Kakembo and Rowntree, 2003; Valentin *et al*., 2005; Boardman and Foster, 2008). This problem is predominant in South African communal landscapes owing to historical environmental and political neglect. The results of this study confirm this trend and indicate that the occurrence of gullies with the associated high soil loss is attributed to low vegetation cover (e.g. Le Roux and Sumner, 2012; Marakanye, 2016). Livestock grazing is a major land use in the study area and degraded grasslands and cattle pathways were observed along lower slope during field data collection. Degraded grasslands are characterised by areas with disturbed soils, possibly due to overgrazing and trampling effects as witnessed in other parts of South Africa (e.g. Kakembo and Rowntree, 2003; Le

Roux and Sumner, 2012). A study by Tamene *et al*. (2006) found that gully erosion favours lower slopes with low vegetation cover as they are more accessible to livestock and human disturbances than steep slopes. However, despite the noticeable trend between gully occurrence and the surrounding vegetation cover, the results of the study indicate a poor correlation between soil loss and vegetation cover. While some studies generally find positive relationship between soil loss and low vegetation cover, this observation could suggest that the role of vegetation cover is masked as the estimated soil loss was measured from present day gully volumes.

Gullies in the study area were observed along drainage lines which were formed in a network of gullies extending upslope. TWI and SPI are associated with upslope contributing area and these areas are characterised by a convergence zone where planform curvature is concave thereby initiating gullies, due to the increased runoff volume downslope (Mathis, 2007; Marakanye and Sumner, 2017). The results of this study indicate that the occurrence of gullies and hence higher soil loss to favour areas with high TWI values mainly on gentle slopes. This is caused by the high moisture content and thus the soils become too weak to hold together (Le Roux and Sumner, 2012). The results of this study are supported by the studies of Kakembo *et al*. (2009) and Kheir *et al*. (2007) who reported that gullies mainly occur on gentle slopes where the upslope contributing area is high and is associated with high TWI values. For instance, Kheir *et al*. (2007) found that gully initiation predominately occurred in areas with high TWI values (>0.4). This represents zones of saturation with high runoff along drainage paths where critical drainage areas are high and slope is low. Likewise, the results of the SPI in this study are consistent with those of Kakembo *et al*. (2009) and Mararakanye and Sumner (2017) who found high SPI values to be associated with gully initiation, due to the high energy potential available to transport sediments.

3.6. Conclusion

In this study, the potential of Sentinel-2 MSI in mapping the spatial distribution of gullies in Okhombe, Drakensberg, South Africa was assessed. The findings of this study have shown that the freely and readily available data offered by Sentinel-2 MSI is effective in providing accurate information on the spatial distribution of gullies, achieving an overall classification accuracy of 77%. The study further showed that gully erosion varies with different environmental variables. Although the were no significant differences between the estimated gully volumes and environmental variables, the study found that gully erosion with the associated soil loss favours gentle slopes contrary to the argument that steep slopes favour gully erosion around the world. Additionally, it was also found that low vegetation, areas with high TWI and SPI values favour gully erosion as this is where drainage lines converge and surface runoff is increased. Overall, the findings of this study should inform land managers and policy makers of the areas in need of rehabilitation and management. Future research should, therefore, aim to use Sentinel-2 MSI as it provides a great potential for mapping and monitoring gully erosion at regional scale. The freely and readily available data makes it an ideal alternative for mapping soil erosion in the resource constrained sub-Saharan Africa for accurate mapping of soil erosion for monitoring and providing remedies of environmental problems (Sepuru and Dube, 2018). Future studies should also investigate other possible environmental variables that could lead to gully development as gully erosion is a complex phenomenon influenced by various environmental variables.

CHAPTER FOUR

Objectives reviewed and Conclusion

4.1. Introduction

The primary focus of this research was to assess remote sensing applications for detecting and mapping the spatial distribution of gully erosion in a communal landscape of Okhombe Valley, Drakensberg, South Africa. In this chapter, the aim and objectives presented in Chapter 1 are reviewed against findings. Furthermore, the chapter also highlights the major conclusions and recommends for potential prospects for soil erosion research.

4.2. Reviewing objectives

4.2.1. Reviewing the progress of remote sensing users and usage for soil erosion monitoring.

Although remote sensing has made great progress in soil erosion monitoring over the years, existing information on the usage and users of remote sensing is poorly documented. This literature review therefore evaluated the usage and the users of remote sensing by focusing on three aspects of the material: publication details, geographic information and data usage. The findings of the study show a significant increase in the number of publications of remote sensing for soil erosion research and further revealed that remote sensing is becoming accepted by a growing number of scientific disciplines, indicating the effectiveness of remote sensing as a tool for soil erosion monitoring. Furthermore, literature also shows that majority of studies are conducted in semi-arid regions, such as Spain, South Africa and India. However, despite the considerable increase in publications, majority of the studies were conducted by authors affiliated with European institutions, while the contribution of African lead authors is low. This possibly indicates an imbalance of knowledge transfer and technologies from developed countries, drawing attention to the challenges faced by resource constrained regions. Notwithstanding the aforementioned shortcomings, remote sensing advancements have allowed for timely and continuous monitoring of soil erosion at larger scales. Landsat is the most commonly used remote sensing system and although its spatial resolution is a limitation, its multispectral bands and archival data make it ideal for soil erosion detection and monitoring, overcoming the challenges presented by high resolution satellites, such as high acquisition costs and limited spectral resolution. The review shows the need for more collaborative research with developing regions and emphasises the need to evaluate the potential of the new generation of satellites in detecting soil erosion features, especially for resource constrained regions.

4.2.2. Assessing the potential of Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies.

Gullies have been reported to be significant sediment sources and pose a threat for catchment water resource management. For effective implementation of soil and water resource conservation, the assessment and monitoring of gully erosion is essential. Freely available satellite data have offered a cheaper and accurate alternative for regional soil erosion assessment. Although, high resolution sensors have been effective in detecting small erosion features, these sensors are restricted to a smaller scale, and have high acquisition costs and thus represent challenges for resource-constrained regions. This study therefore evaluated the potential of the freely available Sentinel-2 MSI sensor in detecting and mapping the spatial distribution of gullies. Despite the spectral complexities of gullies, the findings of the study indicated that the performance of Sentinel-2 MSI sensor can be attributed to the sensor characteristics, achieving an overall classification accuracy of 77%. The Sentinel-2 MSI sensor several bands and more specifically, the red edge bands presented improved mapping accuracy capabilities that other multispectral satellite sensors lack which boosted the sensitivity of the sensor, combined with the robust capabilities of the Support Vector Machine classifier. The study further investigated environmental variables (i.e. slope, vegetation cover, TWI and SPI) that could possibly have an influence on the initiation and development of the identified gullies. The findings of the study indicate that TWI had the most influence on gully initiation and volume of soil loss while slope, vegetation cover and SPI had weak influence on the volume of soil loss despite an observable trend of influence. Overall, the findings of the study demonstrate the importance of using the free and readily available multispectral Sentinel-2 MSI data in conjunction with robust non-parametric Support Vector Machine classifier in mapping the spatial distribution of gullies. Furthermore, these results reiterated the importance of investigating environmental variables in understanding the imitation and development of gullies which facilitates in decision making and implementation of control measures.

4.3. Conclusion

Satellite data has become an important and effective tool in providing information on the spatial distribution of gully erosion. In this study, Sentinel-2 MSI sensor was used to assess and map the spatial distribution of gullies in a communal landscape combined with a robust semi-automatic Support Vector Machine classifier. Given the spectral complexity of gullies, this study has demonstrated the effectiveness of the freely available multispectral sensor for mapping the spatial distribution of gullies. The performance of Sentinel-2 can be attributed to its multispectral resolution particularly the red-edge bands which gave room for more spectral separability. Sentinel-2's 5 day temporal resolution further makes it an ideal data source for continuous monitoring of gully erosion at regional scale especially in resource-constrained regions. Moreover, the investigated environmental variables were found to be useful in understanding of the contributing factors for the spatial distribution of gullies in the study area. The implementation of erosion control measures and rehabilitation requires an understanding of the underlying contribution factors therefore, the investigated environmental factors in this study, will be beneficial for land managers to for the prioritization of control and rehabilitation measures.

4.4. Limitations and recommendations

- Although the current study successfully mapped the spatial distribution of gullies, due to the spatial resolution of the Sentinel-2 MSI sensor some gullies could not be detected by the sensor as they were smaller than 10m. Additionally, future studies should investigate combining Sentinel-1 and Sentinel-2 sensors for improving mapping accuracy as SAR data is very sensitive to soil roughness and moisture and could potentially increase the detection of erosion features.
- The spectral complexity of gullies and their surroundings also proved to be challenging, resulting in mixed pixels, due to the similarity of spectral signatures of un-vegetated and vegetated areas thus affecting the classification process. Future studies should explore incorporating vegetation indices for improving accuracy.
- Although the environmental variables information proved to be beneficial in providing an understanding of the spatial distribution of gullies, future studies should incorporate other topography variables that could improve the understanding the influence of topography on the radiation of features (Taruvinga, 2009). For example,

information on soil moisture and other properties would be beneficial in the training data process by identifying the most informative training samples (Mathur and Foody, 2008).

REFERENCES

Abdel-Rahman, E. M., Mutanga, O., Adam, E. E. & Ismail, R. 2014. Detecting Sirex noctilio grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. *ISPRS Journal of Photogrammetry and Remote Sensing*, 88, 48-59.

Adelabu, S., Mutanga, O., Adam, E. E. &. Cho, M. A. 2013. Exploiting machine learning algorithms for tree species classification in a semiarid woodland using RapidEye image. *Journal of Applied Remote Sensing*, 7, 073480.

Aggarwal, S. 2004. Principles of remote sensing. *Satellite Remote Sensing and GIS Applications in Agricultural Meteorology*, 23-38.

Alatorre, L. & Beguería, S. 2009. Identification of eroded areas using remote sensing in a badlands landscape on marls in the central Spanish Pyrenees. *Catena,* 76**,** 182-190.

America, S. S. S. O. 2001. *Glossary of Soil Science Terms.* . Madison, WI: Soil Science Society of America.

Ananda, J. & Herath, G. 2003. Soil erosion in developing countries: a socio-economic appraisal. *Journal of Environmental Management,* 68**,** 343-353.

Angima, S., Stott, D., O'neill, M., Ong, C. &. Weesies, G. 2003. Soil erosion prediction using RUSLE for central Kenyan highland conditions. *Agriculture, Ecosystems & Environment,* 97**,** 295-308.

Baghdadi, N., King, C., Bourguignon, A. & Remond, A. 2002. Potential of ERS and RADARSAT data for surface roughness monitoring over bare agricultural fields: application to catchments in Northern France. *International Journal of Remote Sensing,* 23**,** 3427-3442.

Betts, H. D. & DeRose, R. C. 1999. Digital elevation models as a tool for monitoring and measuring gully erosion. *International Journal of Applied Earth Observation and Geoinformation,* 1**,** 91-101.

Bishop, M. P., James, L. A., Shroder, J. F. & Walsh, S. J. 2012. Geospatial technologies and digital geomorphological mapping: concepts, issues and research. *Geomorphology,* 137**,** 5-26.

Boardman, J. & Foster, I. 2008. Badland and gully erosion in the Karoo, South Africa. *Journal of Soil and Water Conservation,* 63, 121A-125A.

Boser, B. E., Guyon, I. M. & Vapnik, V. N. 1992. A training algorithm for optimal margin classifiers. In Proceedings of the fifth annual workshop on Computational learning theory, 144-152. ACM.

Botha, J. & Fouche, P. 2000. An assessment of land degradation in the Northern Province from satellite remote sensing and community perception. *South African Geographical Journal*, 82**,** 70-79.

Bouaziz, M., Wijaya, A. & Gloaguen, R. 2011. Remote gully erosion mapping using aster data and geomorphologic analysis in the Main Ethiopian Rift. *Geo-spatial Information Science*, 14**,** 246-254.

Buchholz, T., Marconcini, M. & Fernandez-Prieto, D. 2012. On the Effectiveness of Sentinel-2 Data for Land-Cover Mapping: Comparison with Landsat and SPOT Imagery. In *First Sentinel-2 Preparatory Symposium*.

Chan, L. & Costa, S. 2005. Participation in the global knowledge commons: challenges and opportunities for research dissemination in developing countries. *New Library World,* 106**,** 141-163.

Chaplot, V., Le Brozec, E. C., Silvera, N. & Valentin, C. 2005. Spatial and temporal assessment of linear erosion in catchments under sloping lands of northern Laos. *Catena*, 63**,** 167-184.

Chen, S., Su, H., Tian, J., Zhang, R. & Xia, J. 2011. Estimating soil erosion using MODIS and TM images based on support vector machine and a trous wavelet. *International Journal of Applied Earth Observation and Geoinformation*, 13**,** 626-635.

Cyr, L., Bonn, F. & Pesant, A. 1995. Vegetation indices derived from remote sensing for an estimation of soil protection against water erosion. *Ecological Modelling,* 79**,** 277-285.

Daba, S., Rieger, W. & Strauss, P. 2003. Assessment of gully erosion in eastern Ethiopia using photogrammetric techniques. *Catena,* 50**,** 273-291.

Daubenmire, R. F. 1959. A canopy-coverage method of vegetational analysis. *Northwest Science*, 33, 43-64.

De Jong, S., Paracchini, M., Bertolo, F., Folving, S., Megier, J. & De Roo, A. 1999. Regional assessment of soil erosion using the distributed model SEMMED and remotely sensed data. *Catena*, 37**,** 291-308.

De Villiers, J. & Basson, G. 2007. Modelling of long-term sedimentation at Welbedacht Reservoir, South Africa. *Journal of the South African Institution of Civil Engineering= Joernaal van die Suid-Afrikaanse Instituut van Siviele Ingenieurswese,* 49**,** 10-18.

Del Valle, H., Elissalde, N., Gagliardini, D. & Milovich, J. 1998. Status of desertification in the Patagonian region: Assessment and mapping from satellite imagery. *Arid Land Research and Management,* 12**,** 95-121.

Dewitte, O., Daoudi, M., Bosco, C. & Van Den Eeckhaut, M. 2015. Predicting the susceptibility to gully initiation in data-poor regions. *Geomorphology,* 228**,** 101-115.

d'Oleire-Oltmanns, S., Marzolff, I., Tiede, D. & Blaschke, T. 2014. Detection of gully-affected areas by applying object-based image analysis (OBIA) in the region of Taroudannt, Morocco. *Remote Sensing,* 6**,** 8287-8309.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P. & Martimort, P. 2012. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote sensing of Environment*, 120, 25-36.

Dube, T. & Mutanga, O. 2015. Evaluating the utility of the medium-spatial resolution Landsat 8 multispectral sensor in quantifying aboveground biomass in uMgeni catchment, South Africa. *ISPRS Journal of Photogrammetry and Remote Sensing,* 101**,** 36-46.

Dube, T., Mutanga, O., Sibanda, M., Seutloali K. & Shoko, C. 2017. Use of Landsat series data to analyse the spatial and temporal variations of land degradation in a dispersive soil environment: A case of King Sabata Dalindyebo local municipality in the Eastern Cape Province, South Africa. *Physics and Chemistry of the Earth, Parts A/B/C,* 100**,** 112-120.

Dwivedi, R., Sankar, T. R. Venkataratnam, L., Karale, R., Gawande, S., Rao, K. S., Senchaudhary, S., Bhaumik, K. & Mukharjee, K. 1997. The inventory and monitoring of eroded lands using remote sensing data. *International Journal of Remote Sensing,* 18**,** 107-119.

Everson, T. M., Everson, C. S. & Zuma. K. 2007. Community based research on the influence of rehabilitation techniques on the management of degraded catchments. *Water Research Commission*.

Fadul, H. M., Salih, A. A., Imad-eldin, A. A. & Inanaga, S. 1999. Use of remote sensing to map gully erosion along the Atbara River, Sudan. *International Journal of Applied Earth Observation and Geoinformation,* 1**,** 175-180.
Feng, W. W. & Bajcsy, P. 2005. Extracting Topographic Features From Shuttle Radar Topography Mission (SRTM) Images. National Centre for Supercomputing Applications.

Foody, G. M. & Mathur, A. 2004. A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on geoscience and Remote Sensing*, 42, 1335-1343.

Forkuor, G., Dimobe, K., Serme, I. & Tondoh, J. E. 2018. Landsat-8 vs. Sentinel-2: examining the added value of sentinel-2's red-edge bands to land-use and land-cover mapping in Burkina Faso. *GIScience & Remote Sensing*, 55, 331-354.

Frankl, A., Zwertvaegher, A., Poesen, J. & Nyssen, J. 2013. Transferring Google Earth observations to GIS-software: example from gully erosion study. *International Journal of Digital Earth*, 6**,** 196-201.
Frankl, A., Poesen, J., Scholiers, N., Jacob, M., Haile, M., Deckers, J. & Nyssen, J. 2013. Factors controlling the morphology and volume (V)–length (L) relations of permanent gullies in the Northern Ethiopian Highlands. *Earth Surface Processes and Landforms*, 38, 1672-1684.

Frazier, B., McCool, D. & Engle, C. 1983.Soil erosion in the Palouse: An aerial perspective. *Journal of Soil and Water Conservation,* 38**,** 70-74.
García-Ruiz, J. M. 2010. The effects of land uses on soil erosion in Spain: a review. *Catena,* 81**,** 1-11.
Govaerts, B. & Verhulst, N. 2010. *The normalized difference vegetation index (NDVI) Greenseeker (TM) handheld sensor: toward the integrated evaluation of crop management. Part A-Concepts and case studies*. CIMMYT: Mexico.
Granitto, P. M., Furlanello, C., Biasioli, F. & Gasperi, F. 2006. Recursive feature elimination with random forest for PTR-MS analysis of agroindustrial products. Chemometrics and Intelligent Laboratory Systems, 83, 83-90.

Guanglu, L., Klik, A. & Faqi, W. 2004. Gully erosion features and its causes of formation on the (Yuan) land in the Loess Plateau, China. *Gully Erosion Under Global Change. Sichuan Science and Technology Press.* Chengdu, China**,** 131-142.
Haboudane, D., Bonn, F., Royer, A., Sommer, S. & Mehl, W. 2002. Land degradation and erosion risk mapping by fusion of spectrally-based information and digital geomorphometric attributes. *International Journal of Remote Sensing,* 23**,** 3795-3820.
Hawando, T. 2001. Desertification in Ethiopian highlands. Regional senior consultant on environment and natural resource management. In *RALA Report*.
Hoque, M. A. A., Phinn, S. & Roelfsema, C. 2017. A systematic review of tropical cyclone disaster management research using remote sensing and spatial analysis. *Ocean & Coastal Management*, 146**,** 109-120.
Huang, C., Davis, L. & Townshend, J. 2002. An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, 23, 725-749.

Huete, A. R. & Liu, H. Q. 1994. An error and sensitivity analysis of the atmospheric-and soil-correcting variants of the NDVI for the MODIS-EOS. *IEEE Transactions on Geoscience and Remote Sensing,* 32**,** 897-905.
Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). *Remote sensing of environment,* 25**,** 295-309.

Igbokwe, J., Akinyede, J., Dang, B., Alaga, T., Ono, M., Nnodu, V. & Anike, L. 2008. Mapping and monitoring of the impact of gully erosion in Southeastern Nigeria with satellite remote sensing and Geographic Information System. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. XXXVII. Part B8. Beijing 2008.

Iyer, H. 1974. Use of aerial photographs for soil erosion studies. *Journal of the Indian Society of Remote Sensing,* 2**,** 33-45.

Jacobs, J. A. & Henderson, R. 2012. Interdisciplinarity in Recently Founded Academic Journals.

Jain, S. K. & Goel M. 2002. Assessing the vulnerability to soil erosion of the Ukai Dam catchments using remote sensing and GIS. *Hydrological Sciences Journal,* 47**,** 31-40.

Jones, R. & Keech, M. 1966. Identifying and assessing problem areas in soil erosion surveys using aerial photographs. *The Photogrammetric Record,* 5**,** 189-197.

Jungerius, P., Matundura, J. & Van De Ancker, J. 2002. Road construction and gully erosion in West Pokot, Kenya. *Earth Surface Processes and Landforms*, 27, 1237-1247.

Kakembo, V. & Rowntree, K. 2003. The relationship between land use and soil erosion in the communal lands near Peddie Town, Eastern Cape, South Africa. *Land Degradation & Development*, 14, 39-49.

Kakembo, V., Xanga, W. & Rowntree, K. 2009. Topographic thresholds in gully development on the hillslopes of communal areas in Ngqushwa Local Municipality, Eastern Cape, South Africa. *Geomorphology,* 110**,** 188-194.

Kaplan, S., Blumberg, D. G., Mamedov, E. & Orlovsky, L. 2014. Land-use change and land degradation in Turkmenistan in the post-Soviet era. *Journal of Arid Environments,* 103**,** 96-106.

Karale, R., Bali, Y. & Singh, C. 1976. Photo-interpetation for erosion assessment in the beas catchment. *Journal of the Indian Society of Photo-Interpretation,* 4**,** 29-36.

Karami, A., Khoorani, A., Noohegar, A., Shamsi, S. R. F. & Moosavi, V. 2015. Gully erosion mapping using object-based and pixel-based image classification methods. *Environmental & Engineering Geoscience,* 21**,** 101-110.

Karlson, M. & Ostwald, M. 2016. Remote sensing of vegetation in the Sudano-Sahelian zone: A literature review from 1975 to 2014. *Journal of Arid Environments,* 124**,** 257-269.

Kheir, R. B., Chorowicz, J., Abdallah, C. & Dhont, D. 2008. Soil and bedrock distribution estimated from gully form and frequency: a GIS-based decision-tree model for Lebanon. *Geomorphology*, 93, 482-492.

Kheir, R. B., Wilson, J. & Deng, Y. 2007. Use of terrain variables for mapping gully erosion susceptibility in Lebanon. *Earth Surface Processes and Landforms*, 32, 1770-1782.

King, C., Baghdadi, N., Lecomte, V. & Cerdan, O. 2005. The application of remote-sensing data to monitoring and modelling of soil erosion. *Catena,* 62**,** 79-93.

Kohavi, R. & John, G. H. 1997. Wrappers for feature subset selection. *Artificial Intelligence*, 97, 273-324.

Korhonen, L., Packalen, P. & Rautiainen, M. 2017. Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index. *Remote Sensing of Environment*, 195, 259-274.

Kumar, A., Tiwari, K., Dwivedi, R. & Karunakar, D. 1997. Spectral Behaviour And Spectral Separability Of Eroded Lands Using Multi-Sensor Data. *Land Degradation & Development,* 8**,** 27-38.

Kumar, A., Dwivedi, R. & Tiwari, K. 1996.The effects of image scale on delineation of eroded lands using remote sensing data. *International Journal of Remote Sensing,* 17**,** 2135-2143.

Laker, M. C. 2003. Advances in the South African soil classification system. *Soil classification: A global desk reference***,** 201-220.

Lal, R. 2001. Soil degradation by erosion. *Land degradation & development,* 12**,** 519-539.

Lawrence, R. L. & Ripple, W. J. 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. *Remote sensing of Environment,* 64**,** 91-102.

Le Roux, J. 2011. Monitoring soil erosion in South Africa at a regional scale. ARC-ISCw.

Le Roux, J. J. & Sumner, P. 2012. Factors controlling gully development: comparing continuous and discontinuous gullies. *Land Degradation & Development,* 23**,** 440-449.

Le Roux, J., Morgenthal, T., Malherbe, J., Pretorius, D. & Sumner, P. 2008. Water erosion prediction at a national scale for South Africa. *Water SA,* 34**,** 305-314.

Liberti, M., Simoniello, T., Carone, M., Coppola, R., D'Emilio, M. & Macchiato, M. 2009. Mapping badland areas using LANDSAT TM/ETM satellite imagery and morphological data. *Geomorphology,* 106, 333-343.

Lu, D., Batistella, M., Mausel P. & Moran E. 2007. Mapping and monitoring land degradation risks in the Western Brazilian Amazon using multitemporal Landsat TM/ETM+ images. *Land Degradation & Development,* 18**,** 41-54.

Luk, S. H. 1997. Gully erosion and sediment transport in a small subtropical catchment, South China. *Catena,* 29**,** 161-176.

Ma, J., Xue, Y., Ma C. & Wang, Z. 2003. A data fusion approach for soil erosion monitoring in the Upper Yangtze River Basin of China based on Universal Soil Loss Equation (USLE) model. *International Journal of Remote Sensing,* 24**,** 4777-4789.

MacVicar, C. N. 1977. Soil classification. A binomial system for South Africa. Department of Agricultural Technical Services.

Manjoro, M., Rowntree, K., Kakembo, V. & Foster, I. D. 2012. Gully fan morphodynamics in a small catchment in the Eastern Cape, South Africa. *Land Degradation & Development*, 23, 569-576.

Manyatsi, A. M. & Ntshangase, N. 2008. Mapping of soil erosion using remotely sensed data in Zombodze South, Swaziland. *Physics and Chemistry of the Earth, Parts A/B/C*, 33, 800-806.

Mararakanye, N. & Le Roux, J. 2012. Gully location mapping at a national scale for South Africa. *South African Geographical Journal,* 94**,** 208-218.

Mararakanye, N. & Sumner, P. D. 2017. Gully erosion: A comparison of contributing factors in two catchments in South Africa. *Geomorphology,* 288**,** 99-110.

Mararakanye, N. 2016. A comparative study of gully erosion contributing factors in two tertiary catchments in Mpumalanga South Africa. University of Pretoria.

Martınez-Casasnovas, J. 2003. A spatial information technology approach for the mapping and quantification of gully erosion. *Catena,* 50**,** 293-308.

Mather, P. & Tso, B. 2016. *Classification methods for remotely sensed data*. CRC press.

Mathieu, R., King, C. & Le Bissonnais, Y. 1997. Contribution of multi-temporal SPOT data to the mapping of a soil erosion index. The case of the loamy plateaux of northern France. *Soil Technology,* 10**,** 99-110.

Mathis, J. E. 2007. Specific catchment area as a basis of design for precision riparian buffers. Georgia Institute of Technology.

Mayr, A., Rutzinger, M., Bremer, M. & Geitner, C. 2016. Mapping Eroded Areas On Mountain Grassland With Terrestrial Photogrammetry And Object-Based Image Analysis. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences,* 3.

Megahan, W. F., Wilson, M. & Monsen, S. B. 2001. Sediment production from granitic cutslopes on forest roads in Idaho, USA. *Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group,* 26**,** 153-163.

Metternicht, G. & Fermont, A. 1998. Estimating erosion surface features by linear mixture modeling. *Remote Sensing of Environment,* 64**,** 254-265.

Metternicht, G. & Zinck, J. 1998. Evaluating the information content of JERS-1 SAR and Landsat TM data for discrimination of soil erosion features. *ISPRS Journal of Photogrammetry and Remote Sensing,* 53, 143-153.

Meusburger, K., Bänninger, D. & Alewell, C. 2010. Estimating vegetation parameter for soil erosion assessment in an alpine catchment by means of QuickBird imagery. *International Journal of Applied Earth Observation and Geoinformation,* 12**,** 201-207.

Morgan, R. P. C. 2009. *Soil erosion and conservation*. John Wiley & Sons.

Morgan, R. P. C., Rickson, R. J., McIntyre, K., Brewer, T. R. and Altshul, H. J. (1997). Soil erosion survey of the central part of the Swaziland middleveld. Soil Technology, 11, 263-289.

Mutanga, O. & Skidmore, A. K. 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing,* 25**,** 3999-4014.

Nadal-Romero, E., Vicente-Serrano, S. M. & Jiménez, I. 2012. Assessment of badland dynamics using multi-temporal Landsat imagery: An example from the Spanish Pre-Pyrenees. *Catena,* 96**,** 1-11.

Nanni, M. R., Demattê, J. A. M., Chicati, M. L., Fiorio, P. R., Cézar, E. & d. Oliveira, R. B. 2012. Soil surface spectral data from Landsat imagery for soil class discrimination. *Acta Scientiarum. Agronomy,* 34**,** 103-112.

Navone, S. M. & Palacín, E. 2004. Identificacion de la degradacion/desertificacion de las tierras en Santa Maria (Catamarca) a traves del procesamiento de imagenes Radarsat. *Terra,* 18**,** 289-297.

Ndomba, P. M., Mtalo, F. & Killingtveit, A. 2009. Estimating gully erosion contribution to large catchment sediment yield rate in Tanzania. *Physics and Chemistry of the Earth, Parts A/B/C,* 34**,** 741-748.

Okereke, C., Onu, N., Akaolisa, C., Ikoro, D., Ibeneme, S., Ubechu, B., Chinemelu, E. & Amadikwa, L. 2012. Mapping gully erosion using remote sensing technique: A case study of Okigwe area, southeastern Nigeria. *International Journal of Engineering Research and Applications (IJERA),* 2**,** 1955-1967.

Oldeman, L., Hakkeling, R. & Sombrock, W. 1991. Global Assessment of Soil Degradation (GLASOD). *World map of the status of human–induced soil degradation, ISRIC Wageningen*.

Phinzi, K. & Ngetar, N. S. 2017. Mapping soil erosion in a quaternary catchment in Eastern Cape using geographic information system and remote sensing. *South African Journal of Geomatics,* 6**,** 11-29.

Pickup, G. & Nelson, D. 1984. Use of Landsat radiance parameters to distinguish soil erosion, stability, and deposition in arid central Australia. *Remote Sensing of Environment,* 16**,** 195-209.

Pickup, G. & Chewings, V. 1988. Forecasting patterns of soil erosion in arid lands from Landsat MSS data. *International Journal of Remote Sensing,* 9**,** 69-84.

Pimentel, D. & Burgess, M. 2013. Soil erosion threatens food production. *Agriculture,* 3**,** 443-463.

Pimentel, D. 2006. Soil erosion: a food and environmental threat. *Environment, development and sustainability,* 8**,** 119-137.

Poesen, J. 2011. Challenges in gully erosion research. *Landform Analysis,* 17**,** 5-9.

Poesen, J., Nachtergaele, J., Verstraeten, G. & Valentin, C. 2003. Gully erosion and environmental change: importance and research needs. *Catena,* 50**,** 91-133.

Proffiit, A. 1983. Soil Erosion Mapping and Erosion Risk Assessment in North Wales-a Geomorphological Approach. *South African Geographical Journal,* 65**,** 111-123.

Purevdorj, T., Tateishi, R., Ishiyama, T. & Honda, Y. 1998. Relationships between percent vegetation cover and vegetation indices. *International Journal of Remote Sensing,* 19**,** 3519-3535.

Rahman, M. R., Shi, Z. & Chongfa, C. 2009. Soil erosion hazard evaluation—an integrated use of remote sensing, GIS and statistical approaches with biophysical parameters towards management strategies. *Ecological Modelling,* 220**,** 1724-1734.

Rahmati, O., Tahmasebipour, N., Haghizadeh, A., Pourghasemi, H. R. & Feizizadeh, B. 2017. Evaluating the influence of geo-environmental factors on gully erosion in a semi-arid region of Iran: An integrated framework. *Science of the Total Environment,* 579**,** 913-927.

Ranga, V., Van Rompaey, A., Poesen, J., Mohapatra, S. & Pani, P. 2015. Semi-automatic delineation of badlands using contrast in vegetation activity: a case study in the lower Chambal valley, India. *Geocarto International,* 30**,** 919-936.

Ranga, V., Poesen, J., Van Rompaey, A., Mohapatra, S. & Pani, P. 2016. Detection and analysis of badlands dynamics in the Chambal River Valley (India), during the last 40 (1971–2010) years. *Environmental Earth Sciences*, 75, 183.

Ranga, V., Poesen, J., Van Rompaey, A., Mohapatra, S. & Pani, P. 2012. Spatial analysis of badland dynamics in the lower Chambal Valley India. In *EGU General Assembly Conference Abstracts*, 280.

Reusing, M., Schneider, T. & Ammer, U. 2000. Modelling soil loss rates in the Ethiopian Highlands by integration of high resolution MOMS-02/D2-stereo-data in a GIS. *International Journal of Remote Sensing,* 21**,** 1885-1896.

Sanchez-Hernandez, C., Boyd, D. S. & Foody, G. M. 2007. One-class classification for mapping a specific land-cover class: SVDD classification of fenland. *IEEE Transactions on Geoscience and Remote Sensing*, 45, 1061-1073.

Schulze, R. E. 1997. South African Atlas of Agrohydrology and Climatology: Contribution Towards a Final Report to the Water Research Commission on Project 492: Modelling Impacts of the Agricultural Environment on Water Resources: TT82-96. Water Research Commission (WRC).

Sepuru, T. K. & Dube, T. 2017. An appraisal on the progress of remote sensing applications in soil erosion mapping and monitoring. *Remote Sensing Applications: Society and Environment*, 9, 1-9.

Sepuru, T. K. & Dube, T. 2018. Understanding the spatial distribution of eroded areas in the former rural homelands of South Africa: Comparative evidence from two new noncommercial multispectral sensors. *International Journal of Applied Earth Observation and Geoinformation*, 69, 119-132.

Servenay, A. & Prat, C. 2003. Erosion extension of indurated volcanic soils of Mexico by aerial photographs and remote sensing analysis. *Geoderma*, 117, 367-375.

Seutloali, K. E., H. R. Beckedahl, T. Dube & M. Sibanda (2016) An assessment of gully erosion along major armoured roads in south-eastern region of South Africa: a remote sensing and GIS approach. *Geocarto International,* 31**,** 225-239.

Seutloali, K. E., Dube, T. & Mutanga, O. 2017. Assessing and mapping the severity of soil erosion using the 30-m Landsat multispectral satellite data in the former South African homelands of Transkei. *Physics and Chemistry of the Earth*, *Parts A/B/C,* 100**,** 296-304.

Shruthi, R. B., Kerle, N. & Jetten, V. 2011. Object-based gully feature extraction using high spatial resolution imagery. *Geomorphology,* 134**,** 260-268.

Sibanda, M., Mutanga, O. & Rouget, M. 2015. Examining the potential of Sentinel-2 MSI spectral resolution in quantifying above ground biomass across different fertilizer treatments. *ISPRS Journal of Photogrammetry and Remote Sensing*, 110, 55-65.

Singh, B. 1977. Interpretation of satellite imagery for delineation of ravines. *Journal of the Indian Society of Photo-Interpretation,* 5**,** 31-34.

Singh, D., Herlin, I., Berroir, J. P., Silva, E. &. Meirelles, M. S. 2004. An approach to correlate NDVI with soil colour for erosion process using NOAA/AVHRR data. *Advances in Space Research*, 33**,** 328-332.

Singh, D., Meirelles, M. S. P., Costa, G., Herlin, I., Berroir, J. P. & Silva, E. 2006. Environmental degradation analysis using NOAA/AVHRR data. *Advances in Space Research,* 37**,** 720-727.

Smolska, E. 2007. Development of gullies and sediment fans in last-glacial areas on the example of the Suwałki Lakeland (NE Poland). *Catena,* 71**,** 122-131.

Sonneveld, M., Everson, T. & Veldkamp, A. 2005. Multi-scale analysis of soil erosion dynamics in Kwazulu-Natal, South Africa. *Land Degradation & Development*, 16, 287-301.

Stroosnijder, L. 2005. Measurement of erosion: Is it possible? *Catena,* 64**,** 162-173.

Sujatha, G., Dwivedi, R., Sreenivas, K. & Venkataratnam, L. 2000. Mapping and monitoring of degraded lands in part of Jaunpur district of Uttar Pradesh using temporal spaceborne multispectral data. *International Journal of Remote Sensing,* 21**,** 519-531.

Symeonakis, E., Calvo-Cases, A. & Arnau-Rosalen, E. 2007. Land use change and land degradation in southeastern Mediterranean Spain. *Environmental management,* 40**,** 80-94.

Tagil, S. & Jenness, J. 2008. GIS-based automated landform classification and topographic, landcover and geologic attributes of landforms around the Yazoren Polje, Turkey. *Journal of Applied Sciences,* 8, 910-921.

Tahir, M. E. H., Kääb, A. & Xu, C. Y. 2010. Identification and mapping of soil erosion areas in the Blue Nile, Eastern Sudan using multispectral ASTER and MODIS satellite data and the SRTM elevation model. *Hydrology and Earth System Sciences,* 14**,** 1167.

Takken, I., Croke, J. & Lane, P. 2008. Thresholds for channel initiation at road drain outlets. *Catena,* 75**,** 257-267.

Tamene, L., Park, S., Dikau, R. & Vlek, P. 2006. Analysis of factors determining sediment yield variability in the highlands of northern Ethiopia. *Geomorphology*, 76, 76-91.

Taruvinga, K. 2009. Gully mapping using remote sensing: Case study in KwaZulu-Natal, South Africa. University of Waterloo.

Torkashvand, A. M. & Alipour, H. R. (2009) Investigation of the possibility to prepare supervised classification map of gully erosion by RS and GIS. *World Academy Science, Engineering Technology,* 55, 291-293.

Toutin, T. & Cheng, P. 2002. Comparison of automated digital elevation model extraction results using along-track ASTER and across-track SPOT stereo images. *Optical Engineering,* 41**,** 2102-2106.

Uchida, S. 2015. Applicability of satellite remote sensing for mapping hazardous state of land degradation by soil erosion on agricultural areas. *Procedia Environmental Sciences,* 24**,** 29-34.

Valentin, C., Poesen, J. & Li, Y. 2005. Gully erosion: impacts, factors and control. *Catena,* 63**,** 132-153.

Verstraeten, G., Poesen, J., de Vente, J. & Koninckx, X. 2003. Sediment yield variability in Spain: a quantitative and semiqualitative analysis using reservoir sedimentation rates. *Geomorphology,* 50**,** 327-348.

von Maltitz, G. & Evans. J. 1998. Is Tenure the Root Cause and Consequently the Solution to Resource Degradation in the Communal Areas of Rural South Africa? In Proceeding of the International Conference on Land Tenure in the Developing World.

Vrieling, A. 2006. Satellite remote sensing for water erosion assessment: A review. *Catena,* 65**,** 2-18.

Vrieling, A., Sterk, G. & Vigiak, O. 2006. Spatial evaluation of soil erosion risk in the West Usambara Mountains, Tanzania. *Land Degradation & Development*, 17, 301-319.

Vrieling, A., De Jong, S. M., Sterk, G. & Rodrigues, S. C. 2008. Timing of erosion and satellite data: A multi-resolution approach to soil erosion risk mapping. *International Journal of Applied Earth Observation and Geoinformation,* 10**,** 267-281.

Vrieling, A., Rodrigues, S., Bartholomeus, H. & Sterk, G. 2007. Automatic identification of erosion gullies with ASTER imagery in the Brazilian Cerrados. *International Journal of Remote Sensing*, 28**,** 2723-2738.

Wang, G., Gertner, G., Fang, S. &. Anderson, A. B 2003. Mapping multiple variables for predicting soil loss by geostatistical methods with TM images and a slope map. *Photogrammetric Engineering & Remote Sensing,* 69**,** 889-898.

Wang, L., Niu, Z. & Wei, Y. 2007. Erosion detection by remote sensing. *Progress in Geography,* 2**,** 006.

Wang, X., Zhao, X., Zhang, Z., Yi, L., Zuo, L., Wen, Q., Liu, F., Xu, J., Hu, S. & Liu, B. 2016. Assessment of soil erosion change and its relationships with land use/cover change in China from the end of the 1980s to 2010. *Catena,* 137**,** 256-268.

Waske, B., Benediktsson, J. A., Árnason, K. & Sveinsson, J. R. 2009. Mapping of hyperspectral AVIRIS data using machine-learning algorithms. *Canadian Journal of Remote Sensing,* 35, S106-S116.

Wasson, R., Caitcheon, G., Murray, A. S., McCulloch, M. & Quade, J. 2002. Sourcing sediment using multiple tracers in the catchment of Lake Argyle, Northwestern Australia. *Environmental Management,* 29**,** 634-646.

Wessels, K. J., Prince, S., Frost, P. & Van Zyl, D. 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. *Remote Sensing of Environment,* 91**,** 47-67.

Wilson, J. P. & Gallant. J. C. 2000. Terrain analysis: principles and applications. John Wiley & Sons.

Wulf, H., Mulder, T., Schaepman, M. E., Keller, A. & Jörg, P. 2014. Remote Sensing of Soils. *Zurich, Switzerland*, 71.

Xue, J. & Su, B. 2017. Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, 2017.

Zinck, J. A., López, J., Metternicht, G. I., Shrestha, D. P. & Vázquez-Selem, L. 2001. Mapping and modelling mass movements and gullies in mountainous areas using remote sensing and GIS techniques. *International Journal of Applied Earth Observation and Geoinformation*, 3, 43-53.